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A decision framework with nonlinear preferences and unknown weight information for cloud vendor selection

Mohuya Byabartta Kar [a], Raghunathan Krishankumar [b,*], Dragan Pamucar [c], Samarjit Kar [d]

[a] Department of Computer Science and Engineering, Heritage Institute of Technology, WB, India
[b] Department of Computer Science and Engineering, Amrita School of Computing, Coimbatore, Amrita Vishwa Vidyapeetham, TN, India
[c] Faculty of Organizational Sciences, University of Belgrade, Belgrade, Serbia
[d] Department of Mathematics, NIT Durgapur, WB, India

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ABSTRACT

Cloud vendor selection (CVS) is a complex decision-making problem, which actively adheres to human behavior/cognition. The complex nature of the problem is due to personal biases/hesitation, trade-offs among attributes, uncertainty in rating, and the nonlinear relationship among cloud vendors and associated attributes. In recent times, researchers started paying more attention to user/expert behavior, which led to non-linear decision-making. Most of the extant decision models for CVS considered the linear form of decision-making, which is not realistic due to expert opinions' complexity and dynamism. Motivated by the claim, in this paper, a non-linear decision approach is put forward for CVS. Likert scale rating is adopted for rating cloud vendors based on some attributes, which are transformed to polynomial space from the linear fuzzy space. After this, weights of attributes are determined by using CRITIC in the non-linear space. Following this, cloud vendors are ranked in a personalized fashion using the proposed algorithm that encompasses the WASPAS procedure and rank fusion schemes. Finally, a case study is exemplified to validate the usefulness of the decision approach. Comparison and sensitivity analysis showcases the efficacy and robustness of the developed approach.

1. Introduction

Cloud vendor selection (CVS) is an interesting, complex, and uncertain decision-making problem that involves a set of cloud vendors (CVs) who are rated by users/experts based on specific conflicting attributes (Garg, Versteeg, & Buyya, 2013; Gireesha, Somu, Krithivasan, & Shankar Sriram, 2020). As claimed by Gireesha et al. (2020), the complex nature of the problem is due to personal biases/hesitation, trade-offs among attributes, uncertainty in rating, and the nonlinear relationship among cloud vendors and associated attributes. The preferences from experts are uncertain and involve implicit hesitation. To better model the system, non-linear space is considered appropriate rather than linear space (Zamora, Labella, Rodríguez, & Martinez, 2021). Driven by the claim, in this work, a non-linear decision approach is developed for rational CVS. Data remapping to nonlinear space transforms the rating information into a higher dimensionality, where the dynamism of the cognition can be effectively expressed, unlike the traditional linear space. Further explanation can be seen in the upcoming sections. Readers can also refer (Zamora et al., 2021) for clarity on nonlinear preference forms.

Cloud technology is an internet-driven on-demand technology that allows users to acquire services per the pay-as-you-go theme (Buyya, Yeo, Venugopal, Broberg, & Brandic, 2009; Jatoth, Gangadharan, Fiore, & Buyya, 2018). The technology promotes firm value and multi-domain operations with flexibility (Basole & Park, 2019), (Robertson, Fossaceca, & Bennett, 2021). Popular services from the cloud are software, platform, and infrastructure. In general, X aaS, meaning X as a service (Armbrust, Fox, Griffith, Joseph, & Katz, 2010). COVID-19 pandemic has transformed the work culture globally. As a result, cloud technology gained abundant popularity. The compound annual growth rate increased by 17.5 %; (with software services) from the cloud growing

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* Corresponding author.
E-mail addresses: mohuya.byabartta@heritageit.edu (M. Byabartta Kar), r_krishankumar@cb.amrita.edu (R. Krishankumar), samarjit.kar@maths.nitdgp.ac.in (S. Kar).

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Abbreviation

Abbreviations	Expansions
CVS	Cloud vendor selection
CRITIC	Criteria importance through intercriteria correlation
WASPAS	Weighted aggregated sum product assessment
MADM	Multi-attribute decision-making
CVs	Cloud vendors
EVA	Extreme value amplification
AHP	Analytic hierarchy process
VIKOR	Viekriterijumsko kompromisno rangiranje
CODAS	Combinative distance based assesment
PROMETHEE	Preference ranking organization method for enrichment evaluation
COPRAS	Complex proportional assessment
DEMATEL	Decision-making trial and laboratory
ANP	Analytic network process
TOPSIS	Technique for the order of preference by similarity to an ideal solution
MOORA	Multiobjective optimization by ratio analysis
FUCOM	Full consistency method
DEA	Data envelopment analysis
MARCOS	Measurement alternatives and ranking according to compromise solution
SWARA	Step wise weight assessment ratio analysis
DEs	Decision experts
CSMIC	Cloud service measure initiative consortium

three folds. There is an increase of about USD 60 billion in the cloud market because of the pandemic (https://www.marketsandmarkets.com/ Article no. – 86614844; Dated – 07.08.2021). A report from ENISA stated that almost 68 % of the firms feel optimistic about the cloud as a viable option over traditional IT. From these reports, it is clear that cloud technology is becoming the core urge for development in many organizations, and hence, cloud vendors (CVs) are growing at a faster pace.

Furthermore, existing CVs are creating attractive services and offers to meet user demand. In this high-end competing domain, systematic selection of an apt CV becomes substantial. For this, multi-attribute decision-making (MADM) is considered a viable concept (Anbuudayasankar et al., 2020).

1.1. Motivation and contributions

Recent reviews from Whaiduzzaman et al. (Whaiduzzaman et al., 2014), Masdari & Khezri (Masdari & Khezri, 2020), and Sun et al. (Sun, Dong, Khadeer, Khadeer, & Chang, 2014) on CVS using MADM models inform readers that *(i)* fuzzy-based MADM is very popular for CVS; *(ii)* analytical hierarchy process and TOPSIS are commonly adopted ranking method for CVS; and *(iii)* weights of attributes are considered in the process – either calculated or directly obtained. Some *research challenges* that can be identified from these reviews are *(i)* preferences provided by experts are considered to be linear in nature, which is less reasonable owing to the cognition of experts that is generally dynamic and poses a nonlinear behavior; *(ii)* interaction among attributes are not properly explored along with the importance of experts; that is considered to be an essential parameter during weight estimation owing to the acquisition of rating information from experts; and *(iii)* user or expert centric ranking is lacking in the extant CVS models that reduces the sense of personalization and individual's ranking thereby allowing only cumulative rank estimation of CVs. Motivated by such challenges, the following contributions are proposed, which attempt to alleviate the challenges.

- Non-linear fuzzy remapping is put forward by gaining inspiration from the works in (Delic, Ricci, & Neidhardt, 2019; Zamora et al., 2021). This not only adds rationale to the preference articulation process, but also handles uncertainty effectively in CVS process. These works argue that the process of preference sharing involves cognition of experts that is dynamic and nonlinearly associated; so a nonlinear transformation is effective during decision-making. Initially, a Likert scale-based rating is provided by experts that are converted to its respective fuzzy values that are finally remapped to a polynomial space for MADM. Works done by scholars in (Delic et al., 2019; Zamora et al., 2021). clearly states that *"preferences from experts do not follow linear scales and to better model the nonlinear behavior of experts during preference articulation, nonlinear functions are put forward"*. Polynomial function is one such nonlinear function that remaps the traditional linear scales to nonlinear space for better representing the dynamic nature of experts in the decision process.
- Furthermore, it can be inferred from Gireesha, Kamalesh, Krithivasan, and Sriram (2022) that the *relationship between CVs and the QoS attributes is nonlinear in nature*. Hence, the concept of nonlinear decision making that considers nonlinear preferences for decision-making is suitable for CV selection problem.
- CRITIC approach is extended to extreme value amplification (EVA) scenario in the nonlinear space by remapping the fuzzy preferences with the help of Eq.(6) to effectively capture the interaction among competing attributes considered for CVS along with the importance of experts that is considered as a potential information during weight estimation.
- A new algorithm is developed with the EVA data form from the polynomial remapping, which encompasses the WASPAS approach and fusion scheme for obtaining both holistic ranking and personalized expert centric ranking.
- Finally, a real case study of CVS in an academic institution is presented to testify the usefulness of the proposed nonlinear decision approach.

The rest of the paper is as follows. Existing works on CVS, CRITIC, and WASPAS are described in Section 2. Later, the core implementation of the framework is presented stepwise in Section 3. An example of CVS in a real case situation is provided to clearly demonstrate the usefulness of the integrated approach. Comparison with earlier models both in terms with application and method is provided in Section 5 to better understand the efficacy of the work. Finally, conclusion with shortcomings of the present work, implications, and future directions are provided in Section 6.

2. Literature review

2.1. CVS using MADM approaches

Sun et al. (2014), Masdari and Khezri (2020), and Whaiduzzaman et al. (2014) prepared a review on CVS. They inferred that the decision approaches are practical tools for CVS as there are multiple attributes associated with the selection, and each attribute competes with one another. These reviews showcase the efficacy of the fuzzy sets to handle uncertainty, decision approaches to arrive at rational decisions, and the importance of CVS in IT sectors. It can also be observed that methods such as AHP and TOPSIS are commonly used for CVS and adoption of Likert scale for rating is predominant in the earlier studies.

To carry the theme forward, the authors briefly present some reviews related to CVS. Lang et al. (Lang, Wiesche, & Krcmar, 2018) made an interesting review of diverse attributes that are used for CVS. Jatoth et al. (Jatoth et al., 2018) extended the AHP technique to a fuzzy environment for performing CVS. Krishankumar et al. (Krishankumar, Ravichandran, & Tyagi, 2018) gave a CVS framework under intuitionistic fuzzy (IF) setting by extending variance and VIKOR approach. Psychas et al. (Psychas et al., 2020) provided a toolkit for cloud technology management by application profiling and prediction based on quality of experience factors that enabled proper selection and deployment of IaaS in the cloud context. Dahooie et al. (Dahooie, Vanaki, & Mohammadi, 2019) extended the CODAS technique for CVS in Tehran academic sector under the interval IF setting. Works presented in (Ramadass et al., 2020; Sivagami et al., 2019; Bairagi et al., 2022) developed an integrated CVS approach under the generic linguistic setting by formulating weight calculation and ranking techniques with PROMETHEE and COPRAS techniques. Tang & Liu (Tang & Liu, 2015) came up with a novel approach named function, audit, governance, and interoperability to select trusted cloud sources. Sharma & Sehrawat (Sharma & Sehrawat, 2020) achieved CVS under fuzzy context by using SWOT-DEMATEL combination. Al-Faifi et al. (Al-Faifi, Song, Hassan, Alamri, & Gumaei, 2019) performed CVS with a hybrid technique encompassing clustering and DEMATEL-ANP with smart data. Sun et al. (Sun, Dong, Khadeer, Khadeer, & Liu, 2019) presented a Choquet integral-nonlinear programming integrated approach for CVS with proper attribute interaction. Lai et al. (Lai et al., 2020) introduced Z number-based double normalized aggregation with Gini index for weight assessment under sustainable CVS context. Sivagami et al. (Sivagami et al., 2021) used the interval variant of the generic linguistic set as preference data. They presented a twofold decision approach with data preprocessing and CVS by extending the comprehensive technique and Maclaurin function. Hussain et al. (Hussain et al., 2020; 2020) developed frameworks for CVS under the crisp and fuzzy setting that integrates Pareto mechanism to reduce initial solution space and best-worst technique with fuzzy variants by considering service and experience measures. Recently, Kumar et al., (Kumar, Shameem, & Kumar, 2022) presented a hybrid model for rank prediction with the help of fuzzy AHP and TOPSIS to determine criteria weights and rank values of CVs by considering fuzzy preferences. Hussain & Chun (Hussain & Chun, 2022) came up with a scrutiny and selection framework of CVs by adopting multi-aggregation, best-worst method, and two way consensus mechanism. Ismail, Alrashidi, and Moustafa (2022) presented MACBAC method with neutrosophic environment for assessing risk of CVs in firms through ambidexterity theory. Rahmi (2022) prepared an integrated approach with rank order centroid and CODAS with uncertain preferences for assessing CVs performance for migration of IT activities. Thasni, Kalaiarasan, and Venkatesh (2022) put forward an TOPSIS ranking method with interval-valued fuzzy rating data for evaluating CVs based on the security and accountability attributes. Nejat, Motameni, Vahdat-Nejad, and Barzegar (2022) adopted requirement interval to filter user uncertain requirement and utilized AHP method for ranking CVs for IT migration. Mandal and Khan (2022) presented CoCoSo approach with cloud model for assessing CVs based on the trust aspect measured via QoS attributes.

Table 1 describes the research lacunae that exists in the extant CVS models. From the table, it is clear that there is an urge for an integrated framework that could handle the issues effectively for rational CVS. The table adds value/support to the challenges pointed above and the contributions in this paper attempts to circumvent these challenges.

2.2. CRITIC approach

The idea to capture interrelationship between criteria formed the base for the CRITIC approach (Diakoulaki, Mavrotas, & Papayannakis, 1995; Mukhametzyanov, 2021). The ability of the CRITIC approach gained attention in the research community, and many scholars used the same for criteria weight estimation in diverse fuzzy context. The authors present some recent and relevant works from the literature pertaining to CRITIC. Rostamzadeh et al. (Rostamzadeh, Ghorabaee, Govindan, Esmaeili, & Nobar, 2018) assessed the risk in sustainable supply chains with an integrated fuzzy CRITIC-TOPSIS combination. Babatunde & Ighravwe (Babatunde & Ighravwe, 2019) gave a combination of CRITIC-WASPAS for renewable energy assessment with techno-economic factors. Peng et al. (Peng, Zhang, & Luo, 2019) ranked 5G industries with the CRITIC-CoCoSo combination with Pythagorean fuzzy data. Tus & Adali (Tuş & Aytaç Adalı, 2019) prepared a CRITIC-WASPAS combination with fuzzy data to evaluate software in an organization that performed attendance and time monitoring processes. Wu et al. (Wu, Zhen, & Zhang, 2020) presented an improvement to CRTIC with a cloud model for safety operation assessment in urban rail transit. Rani et al. (Rani, Mishra, Krishankumar, Ravichandran, & Kar, 2021) gave a CRITIC-MULTIMOORA integrated model for food waste treatment selection with neutrosophic information. Wei et al. (Wei et al., 2020) assessed the

Table 1
Summary of features of existing CVS models.

Sources	Dynamism in preferences	Experts' reliability during weight determination	Variability	Interrelationship among criteria	Personalized ranking
Jatoth et al. (2018)	No	No	No	No	No
Krishankumar et al. (2018)	No	No	Yes	No	No
Psychas et al., (2020)	No	No	No	No	No
Dahooie et al. (2019)	No	No	No	Yes	No
Ramadass et al. (2020)	No	No	Yes	No	No
Sivagami et al. (2019)	No	No	Yes	No	No
Pour et al., (2019)	No	No	No	No	No
Sharma & Sehrawat, (2020)	No	No	No	Yes	No
Al-Faifi et al. (2019)	No	No	Yes	Yes	No
Sun et al. (2019)	No	No	No	Yes	No
Lai et al. (2020)	No	No	Yes	No	No
Sivagami et al. (2021)	No	No	Yes	Yes	Yes
Hussain, Chun, and Khan (2020a)	No	No	Yes	No	No
Hussain et al. (2020b)	No	No	No	No	No
Kumar et al. (2022)	No	No	No	No	
Hussain and Chun (2022)	No	No	No	Yes	No
Ismail et al. (2022)	No	No	No	No	No
Rahmi (2022)	No	No	No	Yes	No
Thasni et al. (2022)	No	No	No	No	No
Nejat et al. (2022)	No	No	No	No	No
Mandal and Khan (2022)	No	No	No	No	No
Proposed	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**

location for electric vehicle charging with CRITIC-GRA under the probabilistic uncertain linguistic setting. Simic et al. (Simić et al., 2020) evaluated road safety based on geometric features by using an integrated CRITIC-FUCOM-DEA-MARCOS framework with fuzzy data. Zizovic et al. (Žižović, Miljković, & Marinković, 2020) gave a modified version of CRITIC in the fuzzy context with a new aggregation function for the decision process.

2.3. WASPAS approach

The main notion of this ranking method is to combine the weighted sum and weighted product of different alternatives to achieve the ordering of alternatives (Chakraborty, Zavadskas, & Antucheviciene, 2015). Inspired by the simplicity and efficacy of the approach, many researchers used the ranking (Mardani et al., 2017). Here, we briefly present some recent literature works. Pamucar et al. (Pamučar, Sremac, Stević, Ćirović, & Tomić, 2019) extended WASPAS to linguistic neutrosophic data for ranking safety advisors involved in the proper transport of hazardous goods. Mishra et al. (Mishra, Rani, Pardasani, & Mardani, 2019) selected a supplier by adopting WASPAS and exponential measure with hesitant fuzzy data. Krishankumar et al. (Krishankumar, Saranya, et al., 2019) provided an integrated framework with probabilistic linguistic data that extends variance and WASPAS for supplier assessment. Krishankumar et al. (Krishankumar, Subrajaa, et al., 2019) developed an integrated model that adopts variance and WASPAS for ranking management strategies in construction firms with double hierarchy data. Ilbahar et al. (Ilbahar, Cebi, & Kahraman, 2020) performed a renewable energy assessment in Turkey by adopting the WASPAS approach in the Pythagorean fuzzy context. Pamucar et al. (Pamucar, Deveci, Canıtez, & Lukovac, 2020) evaluated modes for airport ground access in Istanbul by making a fuzzy combination of level-based weight assessment and WASPAS. Recently, Bausys & Januskivisene (Bausys & Kazakeviciute-Januskeviciene, 2021) ranked different techniques for compressing aerial images in a lossy manner by extending WASPAS to neutrosophic fuzzy numbers. Simic et al. Simic et al., (2021) assessed mode for the last-mile travel of goods by presenting a fuzzy WASPAS approach. Rudnik et al. (Rudnik, Bocewicz, Kucińska-Landwójtowicz, & Czabak-Górska, 2021) came up with the idea of ordered fuzzy numbers and extended WASPAS to evaluate improved projects with the view of managing uncertainty and trend in the data. Bouchraki et al. (Bouchraki, Berreksi, & Hamchaoui, 2021) ordered policies pertaining to customers' claims on drinking water by adopting AHP-WASPAS with fuzzy numbers. Yucenur & Ipekci (Yücenur & Ipekçi, 2021) adopted an integrated SWARA-WASPAS combination under the fuzzy context for marine current plant location selection. Ali et al. (Ali, Mahmood, Ullah, & Khan, 2021) initially fine-tuned the operational laws in an uncertain probabilistic linguistic environment and provided an entropy-WASPAS combination for supplier assessment.

2.4. Inference from the review

Based on the review of earlier works presented above, it is clear that (i) CVS is a complex decision problem that is predominantly viewed from a linear perception; (ii) methods such as AHP, entropy, and deviation are commonly used in the weight estimation of attributes pertaining to CVS; (iii) utility-based methods are used popularly for CVS; (iii) interaction among attributes needs to be well explored; and (iv) personalized prioritization based on individual's choice must also be experimented. These inferences form the basis for the research challenges that the authors attempt to circumvent in this work.

3. Proposed nonlinear decision approach

3.1. Preliminaries

Let us review certain basics of fuzzy set.

Definition 1. (Zadeh, 2004): *Let XT be a fixed set. Set $\overline{AX}$ on XT is the fuzzy set given by,*

$\overline{AX} = (xt, \mu_{\overline{AX}}(xt) | xt \in XT)$(1) where $\mu_{\overline{AX}}(xt) = \mu(xt)$ is the membership grade in the unit interval.

For simplicity, we denote μ_i as the fuzzy number, and the collection of such numbers constitute the fuzzy set.

Definition 2. (Zadeh, 2004): *μ_1 and μ_2 are fuzzy numbers, and some operations are given by*

$$\mu_1 \oplus \mu_2 = (\mu_1 + \mu_2 - \mu_1.\mu_2) \tag{2}$$

$$\mu_1 \otimes \mu_2 = (\mu_1.\mu_2) \tag{3}$$

$$\mu_1{}^c = 1 - \mu_1 \tag{4}$$

$a\mu_1 = 1 - (1 - \mu_1)^a$(5) where $a > 0$, c is the complement.

These operations are rudimentary and aid in building the decision framework with integrated approaches in the nonlinear space.

Definition 3. (Zamora et al., 2021): *If a function $F : [0,1] \rightarrow [0,1]$ satisfies the following properties viz.,*

- F is automorphism in the unit interval;
- F is a C^1;
- $F(z) = 1 - F(1 - z)$ for all z in the unit interval;
- $F'(0)\rangle 1$ and $F'(1)\rangle 1$;
- F is convex in the 1 neighborhood and concave in the 0 neighborhood, then F is extreme value amplification.

The extreme value amplification is that concept that increases the distance between extreme values during the nonlinear deformation by considering data/preferences from experts. From (Zamora et al., 2021), it is clear that the initial rating scale used by an expert is generally linear in nature and there is a need for remapping to nonlinear scales for better modeling the nonlinear behavior.

3.2. Data remapping

Linguistic data in a Likert scale are collected from each expert who provides a particular CV rating based on a criterion. As discussed earlier, it is clear that the process of preference elicitation involves pressure to experts, lack of expertise, and uncertainty/hesitation that can be well modeled by adopting nonlinear mapping (Zamora et al., 2021) to the Likert scale rating from experts. The transformation of preferences to the nonlinear space gives rationality to the decision process. The concept of EVA (Zamora et al., 2021) in the process of remapping is followed for better transformation.

In this study, the authors follow the polynomial transformation of preferences. At first, the Likert rating from experts is obtained that are mapped to their respective fuzzy values/membership grades. Later, the polynomial function is applied to remap the preferences to a higher space that allows rational decision-making with the proper realization of hesitation/uncertainty, as claimed in (Zamora et al., 2021).

$$TF(\mu_i) = \begin{cases} 0.5 - 0.5(1 - 2\mu)^{\beta} \mu \in [0, 0.5) \\ 0.5 + 0.5(2\mu - 1)^{\beta} \mu \in [0.5, 1] \end{cases} \tag{6}$$

Where β > 1.

It is important to understand the difference between linear decision-making and nonlinear decision-making before proceeding forward with the proposed methods. When $\beta = 1$ is set in equation (6), the fuzzy values that can be obtained are associated with the Likert scale rating and they are linear in nature and the decision-making with such values are linear decision-making. In contrary, when $\beta > 1$ is set to equation (6), the fuzzy values that can be obtained are associated with the Likert scale rating and they are nonlinear in nature and the decision-making with such values are nonlinear decision-making. As a well-known example, let us consider supplier selection problem. If experts rate by using Likert scale and fuzzy values with $\beta = 1$ are obtained, then the decision-making is linear in nature. If $\beta > 1$ (as shown in Fig. 1), then the obtained fuzzy values are nonlinear in nature and the decision-making is said to be nonlinear decision-making.

The function in equation (6) is concave in the first half and convex in the other with a strictly increasing curve pattern. Based on experts' initial qualitative rating data, fuzzy grades are obtained that are remapped to the nonlinear space by applying equation (6). These values are further given as input to the next sections for weight and rank determination. The parameter values for β is considered as 2, 5, and 10 by authors and based on Fig. 1, it can be seen that $\beta = 2$ provides a broader spread for preferences that makes it intuitively useful and rational for expressing opinions. It can also be seen that as β increases the the spread narrows with values as 0.035 at $\beta = 2$, 0.007 at $\beta = 5$, and 0.0007 at $\beta = 10$.

3.3. Weight calculation procedure

The weight/importance of each attribute must be calculated methodically to reduce biases and inaccuracies in the decision process (Kushwaha, Panchal, & Sachdeva, 2020; Bozanic, Milic, Tešic, Salabun, & Pamucar, 2021). Commonly used approaches come under either fully unknown category or partially known category of weights. The former does not set any overhead on the expert, while the latter does. An expert often faces hesitation during the rating process and is unable/unwilling to provide information on attributes (Bakır, Akan, & Özdemir, 2021). Entropies (Namdari & Li, 2019) and analytical hierarchy process (Bhowmik, Bhowmik, & Ray, 2020) are commonly used methods in the former context.

These models cannot capture interaction among attributes and are complex. Besides, all these methods work well for linear data, which is non-realistic due to the complexity and dynamism of human cognition (Ali et al., 2021). The main reason for using CRITIC approach can be realized in two folds viz., (i) the interrelationship among attributes can be easily captured and (ii) the variability in the preferences/rating from experts on each attribute can also be determined. The former feature allows authors to model the trade-off that exists during rating process of criteria and the latter feature allows authors to understand the hesitation of experts. Motivated by these features, CRITIC is adopted in the present study. Furthermore, reliability values of experts are not considered in the extant weight calculation models, which acts as potential information due to the fact that the opinion vector on attributes is given by experts. The reason for using CRITIC method is because of two main reasons: (i) the interrelationship among attributes can be easily captured and (ii) the variability in the preferences/rating from experts on each attribute can also be determined. The former feature allows authors to model the trade-off that exists during rating process of criteria and the latter feature allows authors to understand the hesitation of experts.

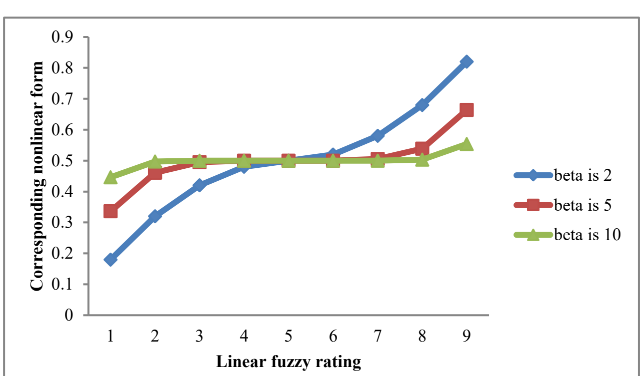

Fig. 1. Data remapping with different parameter values (X axis 1 to 9 denotes 0.1 to 0.9).

Driven by these claims in this section, a new weighted CRITIC approach is put forward for attributes' weight calculation with nonlinearly mapped preference data. Steps for calculation are provided below:

Step 1: Form expert-based opinions of attributes that are linguistically rated by adopting the Likert scale. P vectors of $1 \times n$ order are obtained. As discussed in the previous section, identify the associated fuzzy value to the term and remap the value to the nonlinear space by using Eq. (6).

Procedure presented in Section 3.2 is utilized for remapping the preference information to the nonlinear space that would aid in proper modeling of the behavior of experts. Matrix of order $P \times n$ with nonlinear fuzzy values are obtained for attributes' weight calculation.

Step 2: Obtain reliability values of $1 \times P$ order and apply Eq.(5) to the elements in Step 1 to determine weighted nonlinear preferences.

Step 3: Calculate variance values and correlation coefficients for each attribute using Eqs. (7, 8).

$$V_j = \frac{\sum_{i=1}^{P}\left(wu_{ij} - \overline{wu_i}\right)^2}{P-1} \tag{7}$$

$$C(j1,j2) = \frac{\sum_{l=1}^{P}\left(\left(wu_{lj1} - \overline{wu_{j1}}\right).\left(wu_{lj2} - \overline{wu_{j2}}\right)\right)}{\sqrt{\sum_i\left(wu_{lj1} - \overline{wu_{j1}}\right)^2.\sum_i\left(wu_{lj2} - \overline{wu_{j2}}\right)^2}} \tag{8}$$

where $j1, j2$ are any two attributes, wu_{lj1}, wu_{lj2} are the weighted nonlinear fuzzy numbers, and $\overline{wu_{j1}}, \overline{wu_{j2}}$ are the mean values.

Eq. (7) is applied to determine the variability in the preferences criteria wise based on the views shared by the experts. This is reflecting the hesitation that an expert experiences during the preference articulation process. Generally, if the variability is low, the hesitation is minimum with respect to that criterion. By adopting this equation, the hesitation of experts must be modeled. Besides, the criteria interactions can be effectively captured by adopting Eq.(8). It may be noted that the interaction matrix is a square matrix of $n \times n$ order where each entry denotes the relationship betwwen any two criteria $j1$ and $j2$.

Step 4: Determine the significance factor of each attribute by using Eq. (9), which is further normalized to form weights of attributes (use Eq. (10)).

$$SG_j = V_j.\sum_{j2} C(j1,j2) \tag{9}$$

$$AW_j = \frac{SG_j}{\sum_j SG_j} \tag{10}$$

where SG_j is the significance value, and AW_j is the weight of the attribute.

The formulation provided in Eq. (9) is associated with the significance value of a criterion. The criterion with higher significance gains higher weight as per Eq.(10). Intuitively, any criterion that has considerable interactions with other criteria and incurs certain amount of variability in preferences gains higher significance compared to others, which yields higher relative importance.

3.4. Ranking algorithm

This section deals with a ranking of alternatives that aids in choosing a suitable alternative for the process being considered. As discussed earlier, linear preference spaces cannot capture the dynamism and complexity involved in MADM (Delic et al., 2019; Biswas, Chatterjee, & Choudhuri, 2020; Zamora et al., 2021). Specifically, in this work, the authors look at CVS using a nonlinear WASPAS approach that acquires data as nonlinearly mapped preferences by using a polynomial function.

Based on the review and claims presented above, it is clear that there is an urge for nonlinear ranking methods and so nonlinear WASPAS is developed in this section. It may be noted that there are many ranking methods in the literature, but certain merits of WASPAS that motivated authors to extend the method to nonlinear context are: (i) its simplicity and elegance and (ii) feasible computational complexity motivated authors to extend WASPAS to the nonlinear context. Suppose, m is the number of alternatives, n is the total number of criteria and z is the number of benefit type criteria, complexity of WASPAS is $O(2mn + m)$. For AHP and PROMETHEE the complexity is $O(nm^2)$; for ELECTRE it is $O(mn^2)$ owing to the pairwise comparison. Likewise for VIKOR and TOPSIS, the complexity is $O(4mn + m)$ and for COPRAS the complexity is $O(mz + m(n - z_{+mn} + 2m)$ owing to its formulation dealing with cost type and benefit type criteria separately. From this, it can be clearly inferred that WASPAS is computationally feasible compared to other methods. Hence, WASPAS is chosen in this study.

The procedure for the same is given below

Pseudocode: Ranking with nonlinear data

Input: P decision matrices of $m \times n$ order and attributes' weights of $1 \times n$ order.

Output: Ranking of CVs expert wise and holistic order.

Procedure:

Begin

a. With the nonlinear data from an expert, calculate weighted sum values associated with each CV.
b. Similarly, calculate weighted product values associated with each CV
c. Determine the net rank factor by utilizing values from (a) and (b)
d. Adopt (a)-(c) for all decision matrices
e. Fuse rank vectors from all P experts to form a holistic order

End

$$WTS_i^l = \sum_{j=1}^{n} AW_j.\mu_{ij}^l \tag{11}$$

$$WTP_i^l = \prod_{j=1}^{n} \left(\mu_{ij}^l\right)^{AW_j} \tag{12}$$

where WTS_i^l is the weighted sum value for a CV i based on the data from an expert l, WTP_i^l is the weighted product value for a CV i based on the data from an expert l, AW_j is the weight of attribute j, and μ_{ij}^l is the nonlinearly mapped fuzzy value.

$PT_i^l = \delta WTS_i^l + (1 - \delta)WTP_i^l$(13) where δ is the strategy value, and it can take values from 0 to 1, PT_i^l is the rank value associated with CV i based on data from expert l.

$$NPT_i = \prod_{l=1}^{P} \left(PT_i^l\right)^{DM_l} \tag{14}$$

where DM_l is the weight of the expert l.

It can be observed that Eq. (11) and Eq. (12) form two vectors of $1 \times m$ order that contributes widely to the rank calculation using the proposed method. The values are determined based on each expert's preference information. Moreover, weight value adopted in the formulations are obtained from the procedure described in the previous section. The rank values are determined via the weighted sum and weighted product measures by combinig them with the help of stategy parameter. Specifically, these values are determined for each expert and so P vector of $1 \times m$ order is obtained that is further fused using Eq. (14) to obtain holistic ranks for CVs.

The integrated model in Fig. 2 shows the procedure involved in CVS. The model considers two phases viz., the data collection phase and the methodology phase. In the first phase pre-define qualitative terms are used for rating CVs and the criteria that are used for rating these vendors. Based on the tabular form, the fuzzy grades are associated to each of these terms. Later, nonlinear mapping of these grades are performed with the help of polynomial function described in (Zamora et al., 2021). Matrices from experts pertaining to CVs and criteria are sent as input to the methodology phase where the weights of criteria are determined, which are further used by the ranking algorithm for determining the personalized and cumulative ranks of CVs. This supports rational selection of CV for the problem being considered based on the rank vector obtained by using the calculated weight vector and preference data from each expert.

Before presenting the case example as a demonstration to understand the practical use of the model, it is important to understand the novelty in terms of CRITIC-WASPAS approach in nonlinear context. Specifically, it can be noted that the proposed CRITIC approach under nonlinear context considers reliability values of experts in the formulation, which is lacking in the extant methods. Also, the WASPAS method under

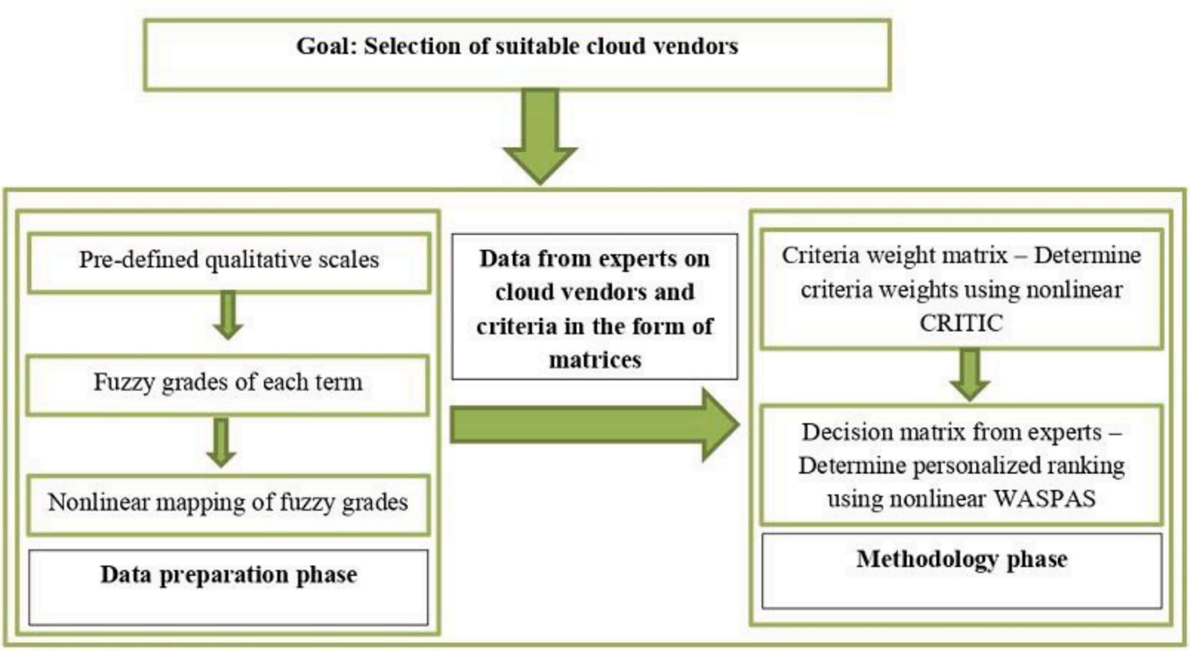

Fig. 2. Integrated nonlinear preference-based decision model.

nonlinear context considers personalized ranking along with cumulative ranking in its formulation, which is also lacking in the extant methods. These innovative novelties of the developed framework adds value to the proposal and aids in rational decision-making.

4. Real case example

This section attempts to exemplify a case example for a better understanding of the usefulness of the framework. For this purpose, a small-medium enterprise named D2O (anonymous name) is considered. The main job of D2O is to offer a recommendation to people about various educational institutes that they can consider for doing their higher education. The company considers a wide range of institutes from India, the USA, Europe, and Australia. The company collects institute-related data from their web page and feedback from different students and faculties regarding the institutes. For allowing open and flexible sharing of ideas/information, names are held anonymous. D2O is a highly data-intensive enterprise that performs analytics based on the data to recommend its customer suitable institutes for pursuing their higher education, based on their needs, scores, interest, and so on.

From the half-yearly report and five-year action plan, it could be noted that the enterprise spends nearly 47 % of its capital on data storage and maintenance. As a result, the ability to hire extra manpower and other commodities such as software and licenses are reducing. The enterprise officials understood this clearly and sought a plan of action that would help them reduce the cost of data storage and maintenance. One potential plan was to adopt cloud technology for data storage and maintenance. When the officials searched for CVs, they found an open source repository called Cloud Armor (https://cs.adelaide.edu.au/~cloudarmor/ds.html) that contains many vendors, and each has a trade-off among their attributes. Officials considered the functional attributes suggested by CSMIC (cloud service measure initiative consortium) as standard benchmark attributes (Csmic, 2012) to be considered while selecting a cloud source. To make a prompt decision, officials outsource decision experts (DEs). There are three DEs viz., senior cloud architect, legal/audit personnel, and a professor with a background in cloud security and networks. These people have a diverse background covering both corporate and academic settings. They are assigned the task of identifying a suitable CV for D2O.

The DEs initially gather and discuss the various alternatives with a brief introduction to each vendor. Based on the Delphi method, nine CVs are chosen for this assignment. Five vendors are chosen as potential candidates based on the interviews over phone calls, video conferences, and transparency of service level agreements. DEs noted that any one vendor is most viable among these five, so each DE rated the CV based on the CSMIC described attributes viz., availability, security, agility, assurance, total cost, and usability (Garg et al., 2013). These six attributes are considered for rating each CV, and it is clear that the initial rating is done linguistically based on the Likert scale that is transformed to the respective fuzzy number and remapped to the nonlinear space for rational decision-making as per the claims from (Zamora et al., 2021), which drives the current study with nonlinear preference space.

Before presenting the steps for rational selection of CVs, let us describe the research problem for clarity to readers. The objective of the study is *to choose a suitable CV from the set of available candidate CVs based on the rating provided by the experts on each CV over diverse attributes by adopting Likert scale grades*. In order to rationally model the nonlinear behavior or experts during the decision process, these grades are fuzzified and remapped to a nonlinear space via the polynomial function. In the present study-five CVs are rated by three experts based on six attributes. Also, these three experts give her/his rating of six attributes for weight determination. Let fs_1 to fs_5 be the set of attributes, cs_1 to cs_5 be the set of CVs, and de_1 to de_3 be the set of experts considered in this study.

Stepwise procedure towards the selection of a suitable CV for D2O is presented below:

Step 1: Three DEs share their rating on five CVs based on six attributes that would eventually form 5×6 matrices for the DEs.

Table 3 presents the data from a different expert in the form of a Likert-scale rating. We adopt nine scale rating with subscripts from 0 to 8. These values are fuzzified using the singleton membership function to obtain their respective fuzzy form. Readers may refer to Table 2 for the same.

Step 2: At the same time, DEs also give their opinion towards each attribute that is used for determining the weights or importance of attributes (refer to Section 3.3). As discussed earlier, these values are Likert scale ratings that are remapped to the polynomial space with $\beta = 2$.

Table 4 shares the opinions of experts on each attribute. This is used for calculating the weights. In this example, officials directly assign the importance of experts as 0.32, 0.34, and 0.34, respectively based on their apriori work knowledge and satisfaction with the team. Initially, the data is remapped to the nonlinear space (refer to Fig. 3), and the procedure discussed in Section 3.3 is applied for determining the weights. The correlation between attributes is shown in Fig. 4 that is considered along with variance to determine the weight vector obtained as 0.01, 0.08, 0.19, 0.11, 0.39, and 0.22, respectively.

Step 3: By using the importance values of attributes and matrices from Step 1, ordering of CVs from each DE's data is obtained. Further, a unified ranking of CVs is also obtained by applying the proposed ranking algorithm (Section 3.4).

Table 5 clearly shows the values associated with each parameter in the ranking method based on each expert's data. Data from de_1 yields an order $cs_3 \succ cs_5 \succ cs_2 \succ cs_1 \succ cs_4$. Data from de_2 yields an order $cs_5 \succ cs_1 \succ cs_2 \succ cs_4 \succ cs_3$. Data from de_3 yields an order $cs_1 \succ cs_3 \succ cs_4 \succ cs_2 \succ cs_5$. By applying Eq. (14), NPT_i is determined as $cs_3 \succ cs_5 \succ cs_2 \succ cs_1 \succ cs_4$, which is considered the net ranking order of CVs.

Step 4: Perform inter/intra sensitivity analysis by varying attributes' weights and strategy values.

It must be noted that new weight vectors are formed by rotation of the attribute weight vector. Six sets (inter sensitivity) are formed that are represented as (a) to (f) in Fig. 5. By varying the strategy values systematically from $\delta = 0.1$ to $\delta = 0.9$ (with unit step size) in each weight set, intra sensitivity is tested. Based on the figure, it is inferred that the *developed framework is robust even after adequate alterations are made* both from the inter/intra perspectives.

5. Comparison study with other works

This section attempts to bring out the efficacy and shortcomings of the proposed framework by performing a theoretical and statistical comparison with extant models. From the application viewpoint, models such as (Hussain, Chun, & Khan, 2020b) and (Sun et al., 2019) are considered. Methodically, to testify the efficacy of the nonlinear WASPAS approach, we compare with (Pamucar et al., 2020) and (Yücenur & Ipekçi, 2021). All these models actively use fuzzy numbers as preference information and follow the linear space of decision-making.

Firstly, we summarize the characteristics of the CVS models to

Table 2
Linguistic terms with associated fuzzy numbers.

Terms	Fuzzy number
None s_0	0
Extremely bad s_1	0.1
Very bad s_2	0.2
Bad s_3	0.3
Neutral s_4	0.4
Good s_5	0.5
Very Good s_6	0.6
Extremely Good s_7	0.7
Perfect s_8	0.8

Table 3
Rating data from experts.

Att.	DEs	CVs for D2O				
		cs_1	cs_2	cs_3	cs_4	cs_5
fs_1	de_1	s_2	s_5	s_7	s_6	s_5
	de_2	s_4	s_4	s_5	s_5	s_7
	de_3	s_6	s_6	s_7	s_6	s_4
fs_2	de_1	s_6	s_3	s_6	s_7	s_7
	de_2	s_3	s_5	s_4	s_7	s_4
	de_3	s_7	s_2	s_2	s_3	s_5
fs_3	de_1	s_7	s_3	s_4	s_1	s_5
	de_2	s_7	s_6	s_1	s_1	s_2
	de_3	s_7	s_7	s_2	s_4	s_7
fs_4	de_1	s_4	s_3	s_1	s_7	s_2
	de_2	s_7	s_3	s_2	s_4	s_2
	de_3	s_4	s_1	s_5	s_3	s_1
fs_5	de_1	s_1	s_4	s_7	s_1	s_3
	de_2	s_1	s_1	s_2	s_2	s_4
	de_3	s_4	s_4	s_6	s_3	s_2
fs_6	de_1	s_1	s_2	s_6	s_3	s_4
	de_2	s_7	s_7	s_3	s_4	s_5
	de_3	s_7	s_3	s_6	s_4	s_2

Table 4
Opinion of an expert on an attribute.

DEs	Attributes					
	fs_1	fs_2	fs_3	fs_4	fs_5	fs_6
de_1	s_5	s_4	s_3	s_6	s_7	s_5
de_2	s_4	s_6	s_3	s_6	s_4	s_6
de_3	s_6	s_2	s_5	s_7	s_3	s_7

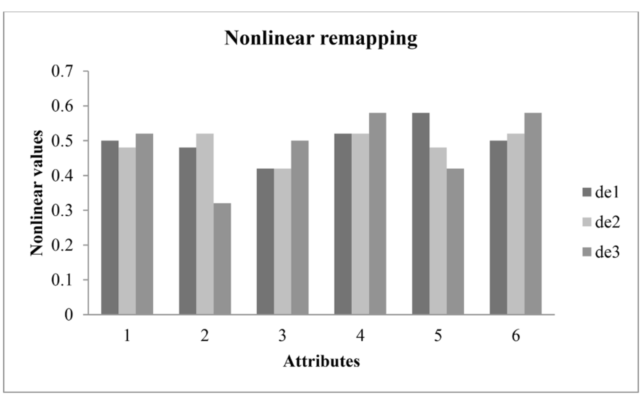

Fig. 3. Mapping of opinions to polynomial space.

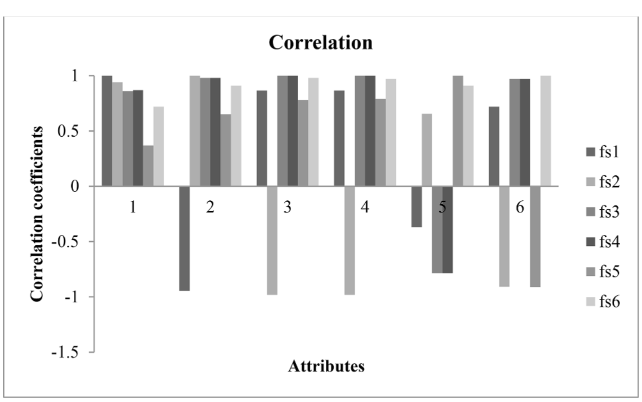

Fig. 4. Interrelationship values among attributes.

understand the efficacy of the proposed work. Table 6 provides the necessary details.

Based on the content from Table 6, some innovations/novelties of the developed framework are inferred:

- As the problem of CVS is complex with diverse competing attributes and nonlinear interactions (Gireesha et al., 2020), (Somu, Kirthivasan, & Shankar, 2017), a nonlinear data remapping is highly substantial, which is considered in the present study. A polynomial function is utilized for data remapping (Zamora et al., 2021).
- With the help of the transformed data, nonlinear interactions among attributes are captured effectively by using the CRITIC approach. Moreover, the hesitation of experts represented via the variability in the preference distribution can also be captured for rational weight assessment.
- Personalized ordering of CVs is obtained based on the expert's viewpoint along with the holistic ordering of CVs, which is lacking in previous models such as (Hussain et al., 2020; Kumar et al., 2022; Sun et al., 2019).
- Unlike the extant frameworks, the proposed model has incorporated consistent fusion of rank values from each expert's data by aggregating rank values via the operator given by Eq. (14). Work from (Liao & Xu, 2015) showcases the simplicity and uniqueness of the operator.
- Moreover, the ranking algorithm can flexibly demonstrate the ordering of CVs from each expert's viewpoint and also holistically for the decision-making process. This flexibility is lacking in the extant models.
- It may also be seen that unlike extant models, in the proposed work, experts' importance are also considered in the formulation of criteria weights, since it is a potential parameter in the decision process and experts are a crucial entity of the preference/opinion sharing process.
- Finally, unlike the previous works (Hussain et al., 2020; Kumar et al., 2022; Sun et al., 2019), the proposed work uses both the reliability values of experts and the importance of attributes during the ordering of CVs that adds rationality in the selection phase.

Besides these value additions, the authors attempt to showcase the efficacy of the work statistically. For this, consistency test and variability test is carried out with respect to proposed versus extant methods (Pamucar et al., 2020; Yücenur & Ipekçi, 2021). The final ranking order of CVs by the proposed method is $cs_3 \succ cs_5 \succ cs_2 \succ cs_1 \succ cs_4$. The proposed model worked with the remapped data. Then, the extant methods (Pamucar et al., 2020; Yücenur & Ipekçi, 2021) are applied, and the order of CVs is obtained as $cs_3 \succ cs_5 \succ cs_2 \succ cs_1 \succ cs_4$. This infers that the *ordering is unchanged, and the correlation coefficient is 1 with statistically significant inference at 95 % confidence*. It also infers that the proposed nonlinear decision model is *consistent* with the extant linear decision models. The extant methods use the data from the linear space for ranking CVs. To further demonstrate the efficacy of the model, a variability test is performed.

300 matrices are generated with order 5×6, and the preferences of each matrix are remapped to the nonlinear space. Rank values are determined for each matrix with the help of proposed and extant methods. As discussed earlier, the strategy values are varied stepwise from 0.1 to 0.9, and the internal variability is determined for these methods. From Fig. 6(a) to (d), it is clear that the proposed method poses an acceptable variability that allows rational discrimination of CVs, indicating that the method is stable. On the contrary, the extant methods (Pamucar et al., 2020) and (Yücenur & Ipekçi, 2021) produce high variability between independent runs (that is, with strategy values), indicating comparatively lower stability. The simulation experiment inferred that *the proposed framework is stable compared to its close counterparts*.

Table 5
Expert driven ranking of CVs with data in nonlinear space.

CVs	de_1			de_2			de_3		
	WTS_i^l	WTP_i^l	PT_i^l	WTS_i^l	WTP_i^l	PT_i^l	WTS_i^l	WTP_i^l	PT_i^l
cs_1	0.316	0.274	0.295	0.409	0.357	0.383	0.528	0.527	0.527
cs_2	0.423	0.419	0.421	0.385	0.341	0.363	0.443	0.424	0.433
cs_3	0.499	0.477	0.488	0.329	0.315	0.322	0.466	0.457	0.461
cs_4	0.309	0.271	0.291	0.366	0.344	0.355	0.446	0.446	0.446
cs_5	0.500	0.446	0.448	0.437	0.430	0.434	0.370	0.351	0.363

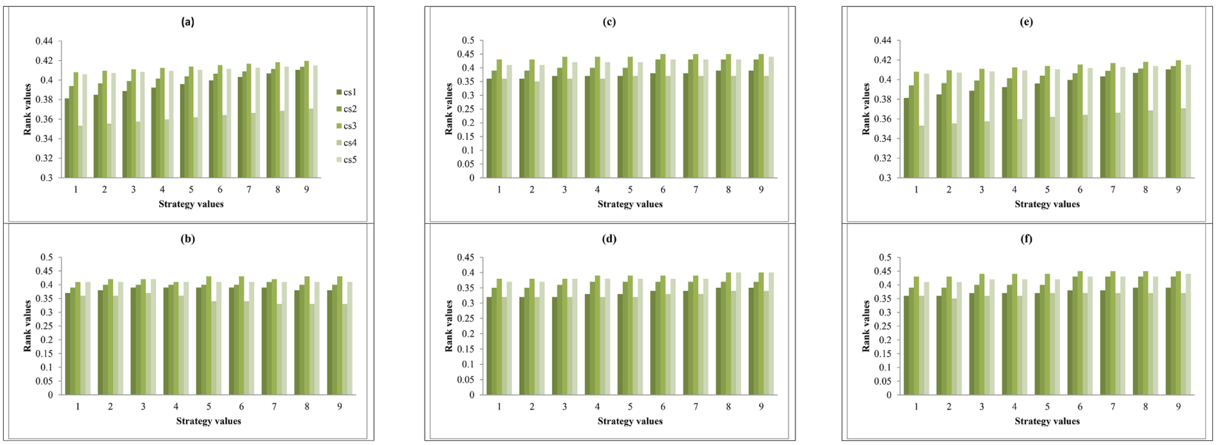

Fig. 5. Inter/intra sensitivity analysis – attributes' weights and strategy values (a) to (f) – Set 1 to Set 6 (X axis 1 to 9 is 0.1 to 0.9).

Table 6
Characteristics summarization for proposed vs other CVS models.

Features	CVS models			
	Proposed	(Hussain et al., 2020)	(Sun et al., 2019)	(Kumar et al., 2022)
Data	Fuzzy numbers			
Remap of data	Done – polynomial function	Not applicable		
Linguistic to fuzzy	Yes			
Interaction among criteria	Captured during weight assessment	Not captured	Captured during preference aggregation	Not captured
Nonlinear criteria relationship	Captured after data remap to polynomial space	Not applicable	Captured in the linear space	Not applicable
Personalized ordering	Done based on data from experts	Not applicable		
Individual/ group ordering	Obtained	Only group ordering is obtained		
Hesitation of experts	Captured during weight estimation	Not captured		
Rank consistency	Ensured during rank fusion	Not applicable		
Consideration of experts' importance	Done during criteria weight estimation and ranking process	Not applicable		

6. Conclusion & future works

The present study is a value addition to the CVS domain. Driven by the inference that linear preference space is unable to handle hesitation more effectively, in this study, a framework for CVS is developed under the nonlinear space. Polynomial remapping of the expert data is carried out at the first step that is further fed as input to the developed framework for assessing attributes' weights and ranking of CVs. To capture the interrelationship among attributes in the nonlinear space, the CRITIC approach is extended. Furthermore, personalized ranking based on expert data is obtained along with the holistic ranking of CVs by adopting an algorithm that includes the WASPAS procedure and a simple weighted geometric operator.

The usefulness of the nonlinear transformation is realized from the variability test, which shows that the proposed model is stable with acceptable variability among independent runs compared to the counterparts that work with linear data. Moreover, a detailed inter/intra sensitivity analysis shows that the proposed work is robust even after adequate changes are made to the weight and strategy parameters. Managerial implications associated with the study are: (i) the proposed model supplements the experts in rational decision-making by considering Likert-scale rating; (ii) the current model supports both the cloud users and the CVs by providing them a mathematical tool that allows them to quantify their decisions; (iii) the model also handles hesitation effectively by remapping the preference data to a nonlinear space; and (iv) managers must be trained for effectively using the framework.

Some limitations of this work are: (i) weights of experts are directly assigned that might sometimes hinder the rationality of the decision process owing to the issues of bias, (ii) interdependencies among experts are not considered during aggregation of preferences; and (iii) the nature of attributes must be considered during ranking for gaining a feel of human oriented decision-making.

Future plans are made to address the limitations of the present study. Later, authors plan to explore the nonlinear preference space such as orthopair contexts (Wang & Garg, 2021; Peng & Luo, 2021) by developing new integrated decision models with nonlinear data for rational

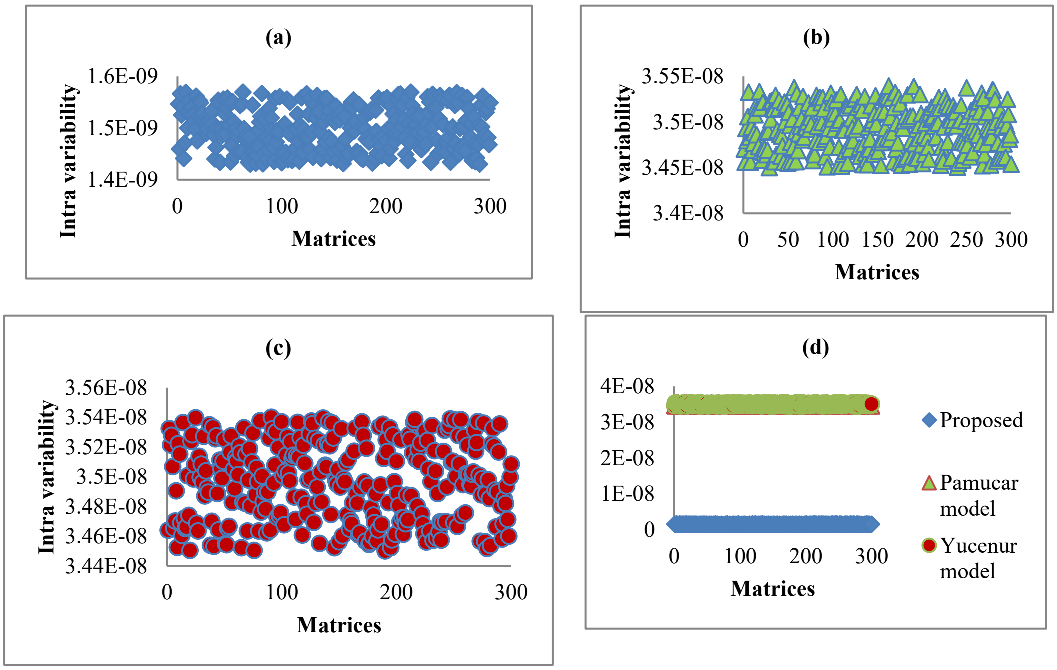

Fig. 6. Scatter plot for variability measure: (a) - Proposed; (b) – Pamucar et al., (2021); (c) – Yucenur et al., (2021), and (d) – combined view.

decision-making and ranking methods from compromise, utility, and outranking categories. Also, the proposed integrated approach can be either directly utilized or ameliorated with preprocessing steps and experts' importance assessment for addressing problems pertaining to business, health, engineering, and environment related decisions. Impact of the parameter β in the nonlinear remap function can be experimented to realize its effects on decision-making Finally, plans to amalgamate recommendation concepts with decision models for achieving large-scale group decisions with customer feedback are made.

CRediT authorship contribution statement

Mohuya Byabartta Kar: Conceptualization, Methodology, Writing – original draft, Writing – review & editing. **Raghunathan Krishankumar:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing. **Dragan Pamucar:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing. **Samarjit Kar:** Methodology, Validation, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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