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Hesitant and uncertain linguistics based executive decision making using risk and regret aversion: Methods, implementation and analysis

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REVIEW HIGHLIGHTS

- Methodology for the newly proposed decision-making technique using IT2 FSs and HFLTSs is provided in detail, with a working illustration on executive decision making.
- The model intakes hesitant-linguistic responses in executive-settings, converts them into IT2 FSs, followed by computation of utility values based on regret theory.
- Comparisons with existing models reveal that the proposed methodology is more user-friendly and also provides relevant and effective ranks.

ARTICLE INFO

Method name:
THREAD stading for **T**ype-2 fuzzy sets, **H**esitancy and **R**egret th**E**ory b**A**sed linguistic **D**ecision making

Keywords:
Multi-criteria decision making
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ABSTRACT

Presence of globally-affecting issues, such as the recent COVID-19 pandemic is a major factor impacting the operation of services provided by high-stake companies. These factors create huge hindrances in the regular and proper operations of companies in staying relevant in market while catering to the services they provide. In such cases, in order to maintain and achieve their internal goals should any possible losses that the grave situation might incur, relevant experts within these firms must arrive at optimal decisions taking into account human cognition as well as all possibilities of risk and regrets. A suitable regret theory based linguistic decision-making model called THREAD which computes with inherent hesitancy using interval type-2 fuzzy sets (IT2 FS) and hesitant fuzzy linguistic term sets-based techniques is introduced in this paper.

Specifications table

Subject area:	Computer Sciences
More specific subject area:	Linguistic Decision Making
Name of the reviewed methodology:	Regret-theory based hesitant fuzzy linguistic executive decision making under type-2 fuzzy uncertainty
Keywords:	Multi-criteria decision making, linguistic decision making, hesitant fuzzy linguistic term sets, linguistic uncertainty, interval type-2 fuzzy sets, regret theory, COVID-19
Resource availability:	Not applicable
Review question:	1. How can hesitant linguistic inputs be handled in the case of executive decision-making in the presence of higher-order uncertainty? 2. Regret and risk aversion is a big factor affecting high-stake decision scenarios such as executive decision-making, especially under challenging times such as the recent COVID-19 pandemic. How to materialize this quest of incorporating methods to handle human psychology within the given decision scenarios?

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Background

The main motivation behind this study was to obtain insights into the realm of executive decision making through the well-established methods of IT2 FSs, HFLTSs and regret theory. While IT2 FSs are the appropriate suitable models to represent linguistic uncertainties arising from human cognition, HFLTS is a remarkable model to handle inherent hesitancy while making choices. Regret theory being one of the most known methodologies to conquer the risk and regret aversive behaviours of individuals, was chosen as the backbone method to handle the same. Since COVID-19 has shaken almost every working industry on this Earth, it is imperative to notice how a certain decision may impact the overall working of the considered company. Keeping in mind the fact that most decision making processes in real life consist of linguistic information predominantly, the aforementioned models fit perfectly the definition of a linguistic decision making model required to handle the high stake decision analysis within companies, operating during pandemics of the likes of the recent COVID-19.

Method details

The requirement of a robust linguistic decision making model that tackles linguistic uncertainties along with the hesitancy of experts providing responses is highly warranted. It is even more crucial in the scenario of executive decision making due to higher stakes and possibilities of catastrophic results in case of uncertain and improper decision making. Along these lines, a linguistic decision making model for risk and regret aversive executive decision making considering linguistic uncertainties and hesitancy is proposed below. The proposed model, called THREAD (short for Type-2 fuzzy sets, Hesitancy and Regret thEory bAsed linguistic Decision making), handles linguistic uncertainties through the employment of the well-known type-2 fuzzy sets (T2 FS) [1-6].

The proposed model of THREAD takes linguistic phrases, or comparative linguistic expressions (CLEs) as inputs. These CLEs represent the true responses of the experts as these expressions map the cognitive understanding of the linguistic information by the decision-making individuals while also allowing them to effeciently output their hesitancy in the form of language. This information in turn is transformed into hesitant fuzzy linguistic term sets (HFLTSs) for effective mathematical computations based on fuzzy sets (FSs). T2 FS based envelopes of these HFLTSs are then computed to capture inherent uncertainties pertaining to the linguistic information, hence increasing the quality of recommendations generated by the proposed model. Subsequently, the projections of these HFLTSs corresponding to every alternative on the ideal reference vectors are computed, followed by the utility values, the regret-rejoice values and the perceived utility values for every alternative. The perceived utility values provide the final ranking of the alternatives based on the experts' input. These final computations shed light on the regret-rejoice behaviour of experts, based on their linguistic inputs for each alternative. The proposed linguistic model is introduced next.

Let the CLEs obtained as the input responses of the expert be denoted by ll_{lj}, where $l \in \{1, 2, ..., m\}$ and $j \in \{1, 2, ..., n\}$. Define the m alternatives and denote them as $\{A_l\}$, $l \in \{1, 2, ..., m\}$, and the n criteria as $\{C_j\}$, $j \in \{1, 2, ..., n\}$. Let the linguistic term set **(**LTS) chosen for generating responses be $S = \{s_0, s_1, ..., s_g\}$.

Each of these responses is a linguistic expression rating the alternatives with respect to all the criteria. The ratings are based on the words given in the pre-decided LTS.

Having assumed the basic information, the steps to perform multi-criteria decision making (MCDM) using the proposed approach are given below:

Step 1: Provide the decision maker with the LTS S and subsequently obtain the decision matrix as given below:

$$D = \begin{bmatrix} ll_{11} & ll_{12} & \dots & ll_{1n} \\ ll_{21} & ll_{22} & \dots & ll_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ ll_{m1} & ll_{m2} & \dots & ll_{mn} \end{bmatrix} \tag{1}$$

Since linguistic expressions in their natural form can not be computed upon, these must be transformed into computation friendly formats, such as HFLTSs, as given below:

Step 2: Apply the transformation function to every CLE ll_{lj}, $l = 1, 2, \dots, m$, $j = 1, 2 \dots, n$ referring to the same defined in [7] to obtain the corresponding HFLTS, $H_{S_{lj}}$ as given below:

$$D' = \begin{bmatrix} H_{S_{ll_{11}}} & H_{S_{ll_{12}}} & \dots & H_{S_{ll_{1n}}} \\ H_{S_{ll_{21}}} & H_{S_{ll_{22}}} & \dots & H_{S_{ll_{2n}}} \\ \vdots & \vdots & \ddots & \vdots \\ H_{S_{ll_{m1}}} & H_{S_{ll_{m2}}} & \dots & H_{S_{ll_{mn}}} \end{bmatrix} \tag{2}$$

Criteria used to judge different alternatives can be of different types. For instance, cost and benefit, which are complementary to each other in meaning. I.e., a higher rating for a cost type criterion is less desirable than that for a benefit type criterion. Therefore, to handle these two types of criteria within our proposed approach, each response is normalized as given next. Usually, the cost criteria are converted into benefit criteria by complementing the responses corresponding to the former type of criterion.

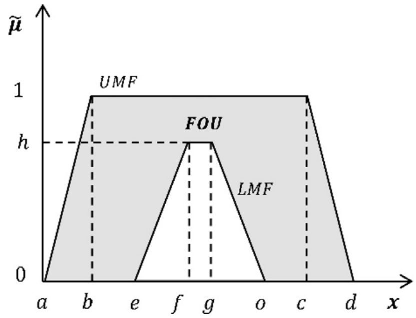

Fig. 1. A T2 FS.

Step 3: Normalize the decision matrix by converting the cost criteria to benefit criteria and obtain the following matrix:

$$D^{N'} = \begin{bmatrix} H^N_{S_{ll_{11}}} & H^N_{S_{ll_{12}}} & \dots & H^N_{S_{ll_{1n}}} \\ H^N_{S_{ll_{21}}} & H^N_{S_{ll_{22}}} & \dots & H^N_{S_{ll_{2n}}} \\ \vdots & \vdots & \ddots & \vdots \\ H^N_{S_{ll_{m1}}} & H^N_{S_{ll_{m2}}} & \dots & H^N_{S_{ll_{mn}}} \end{bmatrix} \tag{3}$$

Once the responses are normalized based on their criteria types, T2 FS based envelopes are computed for each of the HFLTSs representing responses. The T2 FS based envelope of an HFLTS effectively captures the inherent uncertainty associated with the linguistic entity by computing on the entropies of the HFLTS. This envelope consequently aids in further computations, by also retaining the information captured from the true cognitive behaviour of the expert. This step is formally given as follows.

Step 4: For each HFLTS $H^N_{S_{lj}}$ in the normalized decision matrix $D^{N'}$, compute the corresponding T2 FS based envelope as in [7]. Obtain the following decision matrix where each HFLTS is replaced by its representative T2 FS based envelope:

$$D^{env} = \begin{bmatrix} \tilde{F}_{H^N_{S_{ll_{11}}}} & \tilde{F}_{H^N_{S_{ll_{12}}}} & \dots & \tilde{F}_{H^N_{S_{ll_{1n}}}} \\ \tilde{F}_{H^N_{S_{ll_{21}}}} & \tilde{F}_{H^N_{S_{ll_{22}}}} & \dots & \tilde{F}_{H^N_{S_{ll_{2n}}}} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{F}_{H^N_{S_{ll_{m1}}}} & \tilde{F}_{H^N_{S_{ll_{m2}}}} & \dots & \tilde{F}_{H^N_{S_{ll_{mn}}}} \end{bmatrix} \tag{4}$$

Assuming that a T2 FS is represented using the vector $(a_i, b_i, c_i, d_i, e_i, f_i, g_i, o_i; h_i)$ (corresponding T2 FS representation is shown in Fig. 1), the subsequent computations are performed on this vector.

To promote utilization of risk and regret aversive behaviours of the expert, [8] provided techniques computing upon T2 FSs. Their technique processes the projection of the alternatives (through their T2 FS based representations) onto ideal vectors, which is then used to compute the utility values to subsequently obtain regret and rejoice values. These computations are given below.

Step 5: For $\tilde{A} = (\tilde{A}_1, \tilde{A}_2, \dots, \tilde{A}_n)$ as the vector of T2 FSs $l = 1, 2, \dots, m$, ideal reference vector $\bar{A}_r$ compute the projection value for alternative A_l on $\bar{A}_r$ using the following formula:

$$pro_{\bar{\boldsymbol{A}}_r}\left(\tilde{\boldsymbol{A}}_l\right) = \frac{\sum_{l=1}^{n}\left(h_l^2+1\right)}{2n} \times \left[\frac{\sum_{l=1}^{n}\left(a_l+b_l+c_l+d_l\right)+\sum_{l=1}^{n}\left(e_l+f_l+g_l+o_l\right)}{\sqrt{8n}}\right] \tag{5}$$

where, $\tilde{A}_l = (\tilde{F}_{H^N_{S_{l_1}}}, \tilde{F}_{H^N_{S_{l_2}}}, \dots, \tilde{F}_{H^N_{S_{l_n}}})$.

Step 6: Calculate the utility value of alternative A_l, $l = 1, 2, \dots, m$ as follows:

$$v\left(\tilde{A}_l\right) = \left(pro_{\bar{A}_r}\left(\tilde{A}_l\right)\right)^{\alpha} \tag{6}$$

where, $0 < \alpha < 1$ is the risk aversion coefficient of the expert and $\bar{A}_{rj} = (1, 1, 1, 1, 1, 1, 1, 1; 1)$.

Step 7: Obtain the regret-rejoice value of alternative A_l, $l = 1, 2, \dots, m$ using the regret-rejoice function R as follows:

$$R\left(\tilde{A}_l, \bar{A}_r\right) = 1 - e^{\delta(\Delta v)} \tag{7}$$

$$\Delta v = \left(pro_{\bar{A}_r}\left(\tilde{A}_l\right)\right)^{\alpha} - \left(pro_{\bar{A}_r}\left(\bar{A}_l\right)\right)^{\alpha} \tag{8}$$

Here, $\Delta v \leq 0$ and $\delta > 0$ is the risk aversion coefficient.

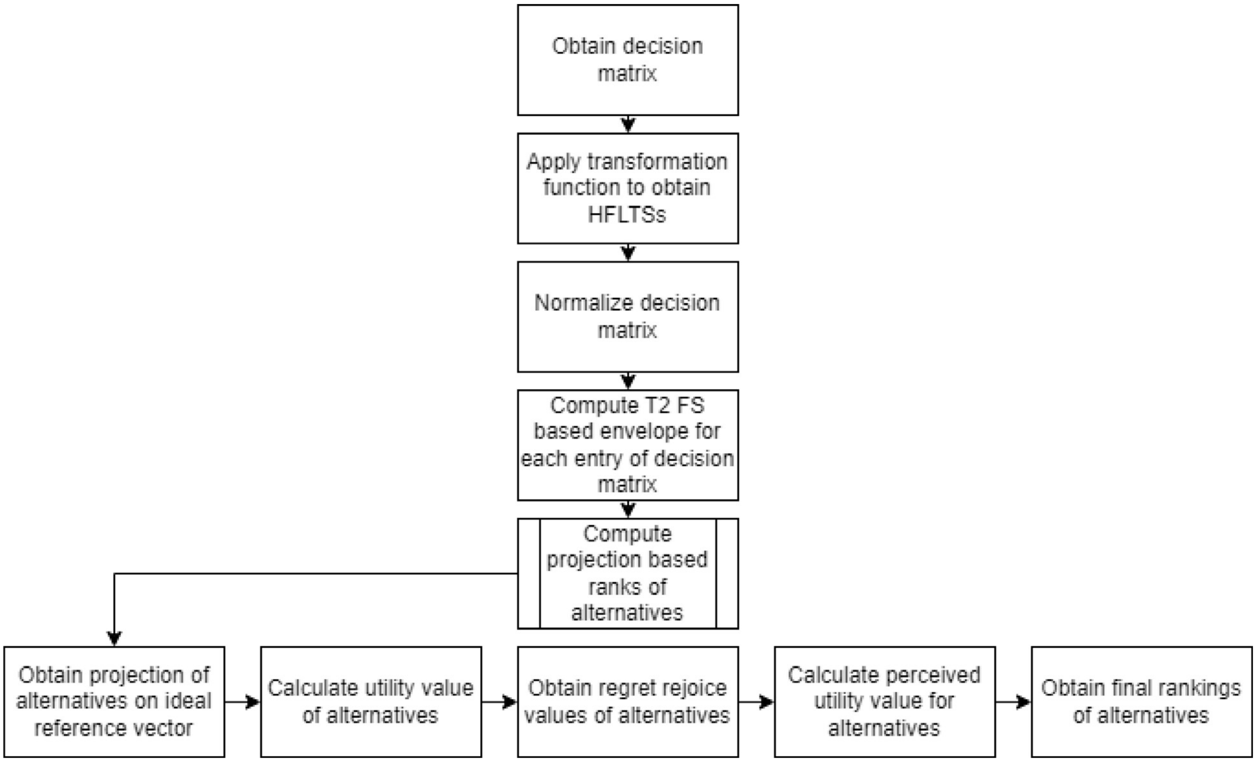

Fig. 2. Flowchart summarizing the proposed linguistic decision making model of THREAD.

Regret is the decision maker's feeling when a sub-optimal alternative is chosen instead of the optimal one, while rejoice is the feeling defined as the additional pleasure obtained when the best alternative is selected.

Also, R is the rejoice value when $R > 0$. Otherwise it reflects the regret value in the other case.

Step 8: Subsequently calculate the perceived utility value for A_l as given below:

$$U\left(A_l\right) = v\left(\tilde{A}_l\right) + R\left(\tilde{A}_l, \bar{A}_r\right) \tag{9}$$

Step 9: Finally obtain the rankings of the alternatives based on the corresponding perceived utility values. Higher value of U demonstrates a higher rank for the corresponding alternative.

The proposed approach for linguistic decision making in the presence of linguistic uncertainties, hesitancy and risk and regret aversive behaviours of an expert can be utlized for high-stake and high-risk decision scenarios such as that of executive decision making. A flowchart summarizing the complete proposed method is presented in Fig. 2. The factors presented above prove the usage of the proposed approach to be desirable in the given scenario. One such example is provided in the next section.

Method validation

An illustration on decision making in a pandemic

It can be easily said that the recent impact of the COVID-19 pandemic has affected millions of people around the world in many ways. Not just humans, but businesses and their models as a whole have also been affected due to the danger of the virus. On the same lines, Gartner, the global research and advisory firm, recently mentioned [9] that executive decision making is key during the recent pandemic situation to be able to put forward effective solutions to help the masses. In its report, Gartner clearly chalked out the three important criteria to be considered while making any executive decisions during the recent pandemic.

Taking inspiration from the above discussion, a scenario for selecting an appropriate executive decision (ED) amongst four candidate EDs is developed. The selection of the optimal ED is conditioned on its impact on the three considered criteria (extracted from [9]): impact on revenue generation, impact on community, and safety. Each of these is a benefit criteria. Since the MCDM model defined can be reused by multiple organizations and institutions, the EDs are kept confidential. The initial parameters of the MCDM model are formally defined as follows:

1. Alternatives: $\{A_1 : ED_1, A_2 : ED_2, A_3 : ED_3, A_4 : ED_4\}$
2. Criteria: $\{C_1 : Revenue, C_2 : Community, C_3 : Safety\}$
3. LTS: $S = \{(s_0 : VeryLow(VL), s_1 : Low(L), s_2 : Moderate(M), s_3 : High(H), s_4 : VeryHigh(VH))\}$

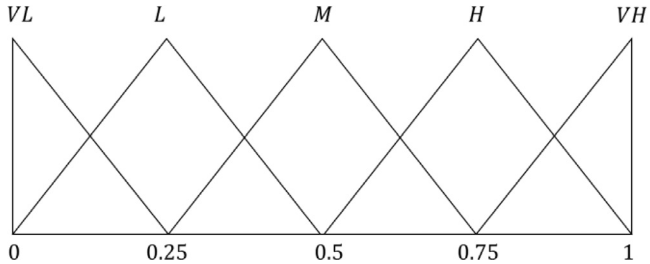

Fig. 3. The LTS utilized by expert.

Table 1
Linguistic responses obtained from expert.

Alternatives & Criteria	$\mathbf{C}_1$: Revenue	$\mathbf{C}_2$: Community	$\mathbf{C}_3$: Safety
A_1 : ED_1	*atleast M*	*M*	*atleast H*
A_2 : ED_2	*between L and H*	*atmost L*	*VH*
A_3 : ED_3	*M*	*atleast H*	*between Land M*
A_4 : ED_4	*atmost M*	*between Mand H*	*L*

The LTS decided upon is depicted pictorially in Fig. 3.

The steps discussed in section of 'Method Details' are utilized to solve the MCDM problem at hand. Details of each of these steps are given below:

Step 1: The set of alternatives, criteria and the LTS are provided to the decision maker to obtain their judgements regarding each alternative against each criteria. The obtained decision matrix is given in Table 1. This decision matrix consists of CLEs as well as single linguistic terms drawn from the LTS S.

Step 2: Using the transformation function, E_{G_H} as defined in [7], the CLEs are transformed into corresponding the HFLTSs $H_{S_{lj}}$, $l = 1, 2, 3, 4, j = 1, 2, 3$. The obtained HFLTSs are given in Table 2.

Step 3: Since each criteria is a benefit criteria, the normalization step is skipped.

Step 4: T2 FS based envelopes, $\tilde{F}_{H_{S_{lj}}}$ are computed for each HFLTS, $H_{S_{lj}}, l = 1, 2, 3, 4, j = 1, 2, 3$ for further computation, based on the method given in [8].

Step 5: With the ideal reference vector, $\bar{A}_r = \{\bar{A}_r j\}, j = 1, 2, 3$, where $\bar{A}_r j = (1, 1, 1, 1, 1, 1, 1, 1; 1)$, the T2 FS based projection value of alternative $A_l, l = 1, 2, 3, 4$ on $\bar{A}_r$ is computed, to obtain the following values:

$$pro_{\bar{A}_r}\left(\tilde{A}_1\right) = 2.3179, pro_{\bar{A}_r}\left(\tilde{A}_2\right)) = 1.8569,$$
$$pro_{\bar{A}_r}\left(\tilde{A}_3\right)) = 1.3542, pro_{\bar{A}_r}\left(\tilde{A}_4\right)) = 0.9639,$$

where, $\tilde{A}_l = (\tilde{F}_{H_{S_{l1}}}, \tilde{F}_{H_{S_{l2}}}, \tilde{F}_{H_{S_{l3}}})$.

Step 6: The utility value of every alternative $A_l, l = 1, 2, 3, 4$ is computed with the risk aversion coefficient value $\alpha = 0.8$ and the following values are obtained:

$$v\left(\tilde{A}_1\right)) = 1.9592, v\left(\tilde{A}_2\right)) = 1.6407, v\left(\tilde{A}_3\right) = 1.2745, v\left(\tilde{A}_4\right)) = 0.9710,$$

where, $\tilde{A}_l = (\tilde{F}_{H_{S_{l1}}}, \tilde{F}_{H_{S_{l2}}}, \tilde{F}_{H_{S_{l3}}})$.

Step 7: The regret-rejoice value for every alternative $A_l, l = 1, 2, 3, 4$ is computed with regret aversion coefficient value $\Delta = 0.3$ and the following values are obtained:

$$R\left(\tilde{A}_1, \bar{A}_r\right)) = -1.4155, R\left(\tilde{A}_2, \bar{A}_r\right)) = -1.6578,$$
$$R\left(\tilde{A}_3, \bar{A}_r\right) = -1.9668, R\left(\tilde{A}_4, \bar{A}_r\right) = -2.2492.$$

Step 8: Next, the perceived utility value of each alternative $A_l, l = 1, 2, 3, 4$ is computed to obtain the following values:

$$U\left(A_1\right) = 0.5437, U\left(A_2\right) = -0.0171, U\left(A_3\right) = -0.6923, U\left(A_4\right) = -1.2782$$

Table 2
Transformed linguistic responses obtained from expert into HFLTSs.

Alternatives & Criteria	$\mathbf{C}_1$: Revenue	$\mathbf{C}_2$: Community	$\mathbf{C}_3$: Safety
A_1 : ED_1	$\{M, H, VH\}$	M	$\{H, VH\}$
A_2 : ED_2	$\{L, M, H\}$	$\{VL, L\}$	VH
A_3 : ED_3	M	$\{H, VH\}$	$\{L, M\}$
A_4 : ED_4	$\{VL, L, M\}$	$\{M, H\}$	L

Step 9: Based on the perceived utility value computed above the rankings of alternatives are obtained as follows:

$$A_1 : ED_1 > A_2 : ED_2 > A_3 : ED_3 > A_4 : ED_4. \tag{10}$$

Therefore, ED_1 is the best executive decision to be considered for execution in the company, considering the impact on the considered criteria.

Comparative analysis with existing models

Comparisions of the proposed THREAD with other existing models from the literature are provided in this section. These are done amongst two models viz. [10] and [8]. These models are chosen to demonstrate different behaviours when compared to the proposed approach, much like an ablation study on the latter.

The problem considered in the previous section is solved using each of the models mentioned above and their results are compared. The rankings obtained using the method in (4:10) are as given below:

$$A_1 : ED_1 = A_2 : ED_2 = A_3 : ED_3 > A_4 : ED_4. \tag{11}$$

Those obtained using the method in [7] are given below:

$$A_2 : ED_2 > A_1 : ED_1 > A_3 : ED_3 > A_4 : ED_4. \tag{12}$$

From the above results, the following observations are made:

1. It is clear that the rankings in Eqs. (10–11) are different. More specifically, the recommendation provided by the model in [10] is ambiguous, i.e. there is no difference in the ratings of three alternative decisions, hence making it impossible to choose the best alternative. Whereas in the proposed approach, clear judgements can be made to obtain the rankings, hence also promoting explanability in arriving at recommendations. This is made possible due to the property of the proposed model being able to capture the linguistic uncertaintites through T2 FS based envelopes along with the handling of risk and regret aversion through projections. These properties make the proposed approach more reliable and desirable in high risk scenarios by providing clear results.
2. Comparing Eq. (10) and (11) also reveals difference in rankings. The ranking differ due to the fact that the proposed model captures the risk and regret aversive behaviours of the expert by computing the projections of the alternatives onto ideal vectors, a point where the model in [10] lacks.

Comparing the proposed THREAD with the one introduced in [8], the following points can be made:

1. While the linguistic decision making model given in [8] does capture the risk and regret aversive behaviours of the expert, it does not model the hesitancy of the expert during the input phase. This leads to incorrect rankings as the cruciality of cognitive behaviours of the expert is ignored as it considers only single linguistic terms as inputs. This isssue is alleviated by the model proposed in this paper.
2. The T2 FS based representation of linguistic information is assumed to be obtained from the expert in [8]. In reality, this may not be the case as not all individuals are apprised with the concept of T2 FSs. This is tackled by the method proposed in this paper as the T2 FS based representations are computed and obtained online from the linguistic inputs collected from the expert as responses. This is especially important in high risk scenarios such as those in executive decision making.

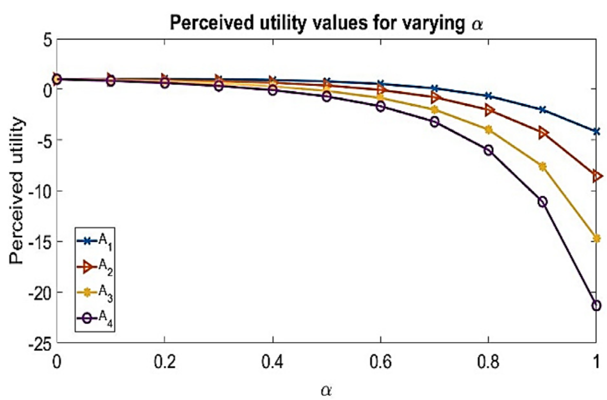

Fig. 4. Values of perceived utility obtained after varying risk coefficient, α.

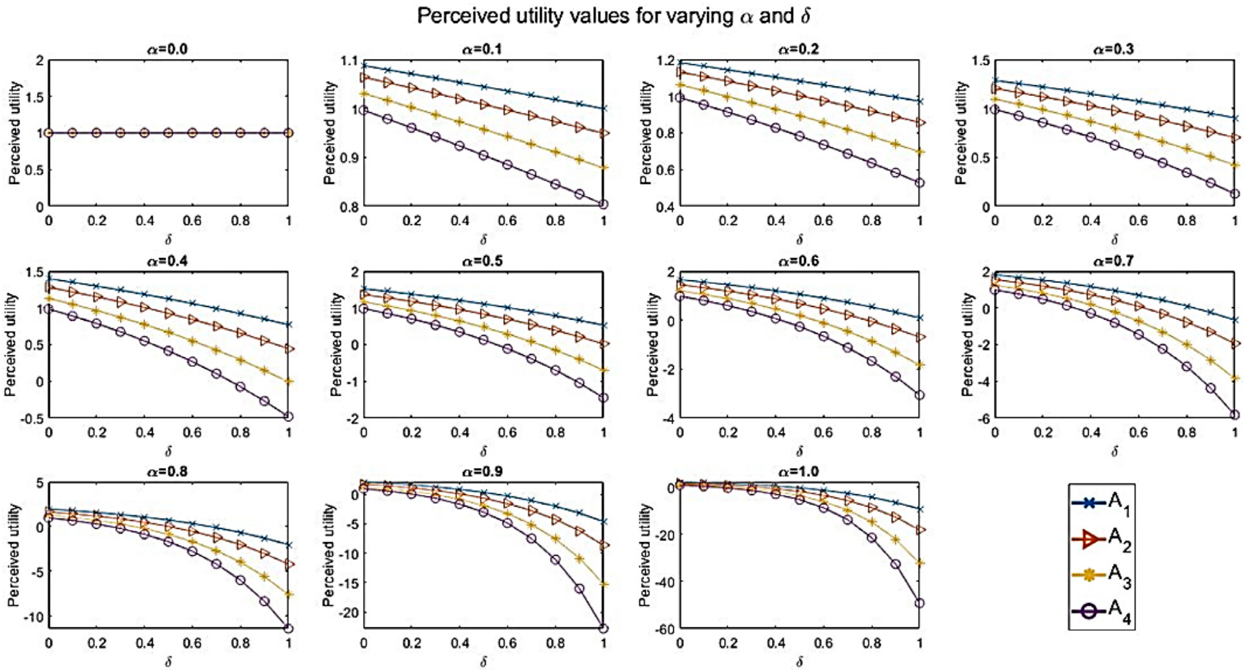

Fig. 5. Values of perceived utility obtained after varying risk coefficient, α and regret coefficient, δ.

Sensitivity analysis

In this section, a sensitivity analysis is performed, based on different values of both, the risk and regret aversion coefficients to demonstrate the performance of the proposed MCDM model. For the analysis, 11 different values ranging from $(0, 0.1, 0.2, \ldots, 1)$ are chosen for both α and δ. The effect of these values on the final perceived utility value for each alternative are studied.

Figs. 4 and 5 show the effect of the sensitivity analysis performed on the risk and regret aversion coefficients on the perceived utility values respectively.

It can be clearly seen from both the figures that rankings of the alternatives remain constant with the changing values of both α and δ. This is because the T2 FS based projection values obtained for the alternatives are in constant order. This observation from the proposed approach is consistent with that in [8].

Conclusion

In this paper, a hesitant fuzzy linguistics, projection and regret theory method, called THREAD, using T2 FSs for executive decision making has been introduced. The proposed method has introduced the concept of HFLTSs in the projection and regret theory concept for MCDM in the T2 FS environment to handle and efficiently model the hesitancy faced by the decision maker while providing his/her responses after judging some given alternatives based on a set of criteria.

The model has enabled the decision makers to respond with more than one linguistic terms. After accepting the linguistic responses from the decision maker, the proposed model has solved the MCDM problem with projection based regret theory to model the psychological behavior of the decision makers.

Working of the proposed model has been demonstrated by means of an illustration of an executive decision making scenario during pandemic impacted global restrictions. A decision maker has judged four alternatives of executive decisions based on three different criteria, impact on revenue generation, impact on community, and safety. Finally, the executive decision, ED_1 is adjudged to be the best decision to be implemented in the recent scenario of pandemic, considering its impact on all the three criteria.

Studies comparing various existing models with the proposed model reveals the edge the latter possesses above the rest. These studies has revealed that the proposed approach is capable of generating explainable recommendations from the linguistic inputs of the expert, while also capturing the hesitancy and the inherent linguistic uncertainties in the input information.

As a future work, the proposed model is being extended to consider T2 FSs from the information representation phase of HFLTS. From another dimension and with the availability of more data on the recent pandemic, more useful scenarios can be modeled using the proposed work, for e.g., diagnosis of diseases based on various symptoms, testing efficiency of vaccines based on results from clinical trials and other factors etc.

Additional information

The unprecedented surge of human-interaction with computing systems for a diversified range of tasks often warrants development of models that are intelligent enough to emulate human behaviour. This is also made possible by the burgeoning amounts of data piling up from different sources at every passing second. Mounts of literature is a proof to this development being made possible by artificial intelligence (AI), e.g. being aiding farmers by enhancing livestock welfare using AI based approaches [11] and machine learning based medical record analysis and COVID-19 detection [12]. So much so that many researchers argue for integrating AI literacy into technological literacy frameworks in education, emphasizing the importance of understanding AI concepts, ethics, and socio-technical implications alongside technical skills like programming, to prepare students for future AI-driven environments and work settings, e.g. in [13].

Apart from these, decision making is one such important aspect in the practical scenario (e.g., such as in usability confirmation of augmented reality in-car systems [14]), when considering human-centric systems which are able to analyze and subsequently emulate the human cognition and human behaviour, often in the presence of uncertainty and bounded rationality. Such concepts are much more evident in the recent works where researchers survey various models and methods from operations research (OR) and machine learning (ML) communities under the umbrella of contextual stochastic optimization, aiming to enhance understanding and encourage advancements in combining prediction algorithms and optimization techniques for decision-making under uncertainty [15], whereas authors of [16], explore the role of decision-making to assess hoteliers' attitudes and preferences towards using AI across various decision-making approaches, identifying clusters of managers based on their acceptance of AI technologies and determining factors influencing their preferences, ultimately highlighting the suitability of AI for specific types of decisions within the hotel industry regardless of personal or property-related characteristics. More technical works of the recent times include [17], whose authors address the challenge of effectively using confidence values provided by binary classifiers in decision-making scenarios. It investigates why decision-makers struggle to trust predictions based on these confidence values and proposes a solution by aligning the confidence values with the decision maker's own confidence in their predictions, ensuring a more rational and discoverable decision policy. Through theoretical arguments and experiments, the paper demonstrates that this alignment can lead to improved decision-making outcomes in AI-assisted decision-making scenarios. More insights on such decision-making models can be obtained from [18].

Due to such demonstrated cruciality of decision analysis, efficient models and mechanisms that promote proper decision making must be developed. During this process of development, the various factors involving human beings must also be taken care of. Such problems require the involvement of humans in many stages and in many roles. One such stage is that of the knowledge elicitation, where the information coming from humans is predominantly linguistic.

To handle this knowledge with linguistic entities (especially words), Zadeh [19] introduced the concept of linguistic variables, eventually followed by the paradigm of computing with words (CWW) [20]. As the name suggests, CWW deals with linguistic entities that are words, in the form of linguistic variables and computes with them.

Handling such qualitative aspects in theory was backed by the theory of fuzzy sets (FS) and fuzzy logic (FL). Hence, the fuzzy linguistic approach (FLA) proved to be beneficial in the domain of CWW, which helped in the development of multiple linguistic models such as the extension principle-based model [21], the symbolic method-based approach [22], the 2-tuple based representation and computational model [23] etc. Each of these models followed the basic strategy of performing computations on words.

These models however suffer from two drawbacks. Each of these models handle linguistic information by means of type-1 (T1) FSs. Moreover, utilizing these models for linguistic decision-making problems restricts individuals from choosing more than one linguistic term as representations of their judgements. These two drawbacks were solved by means of two new theories:

- Type-2 (T2) FSs: The T1 FSs suffer from the issue of interpretability because the membership degrees of a T1 FS are crisp. T2 FSs, first introduced by Zadeh [19] as extensions of T1 FSs, and later made popular by Mendel [24] possess higher degrees of freedom. This enables the T2 FSs to model the uncertainty associated with linguistic entities, namely the linguistic uncertainties, properly. More details on the establishment of T2 FSs can be found in [1].
- Hesitant fuzzy linguistic term sets (HFLTS): The concept of HFLTSs was introduced in the literature by Rodriguez et al. [10] to present the experts with an option to represent their judgments with more than one linguistic term. HFLTSs are useful in situations when experts are hesitant in eliciting one single term to represent their judgement properly. HFLTSs hence gives the freedom of choosing more than one linguistic term in the process of linguistic decision making.

Approaching decision making from a different point of view leads one to the impact of certain behaviours of the experts. Of many, the risk attitude of an expert is of importance in any high-stake decision-making scenario, such as executive decision making in large firms. Prospect theory [25] has aided the study and description of the above. However, more crucial behavioural notions such as the regret/rejoice must be taken into account during the task of decision making. Regret is the feeling that a decision maker feels when they know that the best alternative was not selected. Regret theory [26,27] is an exemplary approach from the branch of economics which provides methods of regret aversion, to arrive at optimal decisions in a given scenario by allowing the proper consideration of the feeling of regret for any decision made. Very recently, regret theory has been utilized for the selection of construction program manager within a project in China [28]. Interestingly, another study [29] combined the theory with a reliability-based consensus model in a group decision making environment for application to sustainable zero-carbon measure prioritization within the Indian transport sector. In another case, a consistency improving decision making method was lately applied to an emergency assistance area selection problem in [30].

Furthermore, a projection-based regret theory method for decision making in the T2 fuzzy environment [8] was presented in the literature. The model presented in [8], introduced T2 FSs into the domain of MCDM with the additional goals of risk as well as regret aversion.

More projection-based regret theory methods were introduced fairly recently, owing to their superior real-life applicability to solve appropriate problems of significant importance. E.g., authors of [31] introduced a sophisticated decision-making framework tailored for uncertain situations in medicine company contexts, where information is often vague and ambiguous. Leveraging Three-way decision (3WD) methods and interval fuzzy information, it introduces the Probabilistic Interval-Valued q-Rung Orthopair Hesitant Fuzzy Set (PIVq-ROHFS) to enhance fault-tolerance and validate decision-maker evaluations. Additionally, it introduces a Regret theory-based 3WD model for utility evaluation and proposes a novel MCDM method utilizing Multi-Objective Optimization (MOO) techniques, including a hybrid PSO-MCGP optimization approach with a utility function, thus providing a comprehensive solution for complex decision-making scenarios in medicine company settings. [32] proposed a novel Emergency Decision Making (EDM) method that combines regret theory and the Evaluation based on Distance from Average Solution (EDAS) method within a 2-tuple spherical linguistic framework. It utilizes 2-tuple spherical linguistic term sets (TSLTSs) for decision-makers to express uncertain evaluations of emergency alternatives, then employs an integrated approach to rank and select the optimal response. The method also objectively determines criteria weights using the CRITIC method and demonstrates its effectiveness in a public health emergency scenario in China, validated through comparative analysis with other EDM methods.

Even though the above models handle many issues in the realm of decision making, they do not address one key issue. These models are not capable of dealing with hesitancy which a decision maker or expert faces while providing his/her judgment for alternatives based on certain criteria. This is especially true in the case of executive decision making due to the highly risky stakes involved, and with each decision costing the involved organization in some way or form. This is evident from the studies such as [33], where it explores how meaningful coincidences can boost executive confidence and improve related decision-making in crisis situations within the Italian hospitality industry, filling a gap in existing literature on crisis management, whereas [34] investigates the relationship between CEO financial expertise and decision-making in 270 Chinese non-financial firms from 2005 to 2021, highlighting the increasing importance of financial literacy for strategic decision-making and long-term competitiveness in a dynamic economic environment. Some related research can also be found in [35,36].

To overcome aforementioned limitation regarding hesitancy and linguistic uncertainty handling within the realm of executive decision-making, we propose a novel hesitant fuzzy linguistic and projection-based regret theory for MCDM using T2 FSs to be used for executive decision making. The proposed model called THREAD is equipped to handle hesitant responses consisting of more than one linguistic terms through the concept of HFLTSs. Decision makers are provided with a LTS, consisting of multiple linguistic terms ordered on a fixed scale. They then choose linguistic terms or CLEs, consisting of more than one linguistic term. For e.g.: ‘between average and good’, ‘at least good’ etc. To compute with such complex linguistic entities, it is important to convert them into simpler representations. This is done through the computation of T2 FS based envelopes for HFLTSs [7].

After obtaining the T2 FS based representations of the HFLTSs, decision making is carried out using the model in [8] using the projection-based regret theory method, to obtain the best alternative based on the linguistic responses of the experts consisting of CLEs and linguistic terms.

Therefore, it can be said that innovation of this proposal lies in introducing a regret theory-based linguistic decision-making model that incorporates T2 FSs and HFLTS based techniques. This model is designed to help high-stakes companies facing globally-affecting issues like the COVID-19 pandemic to make optimal decisions while considering human cognition, risk, and regrets, thus addressing the challenges of maintaining relevance and achieving internal goals during turbulent times.

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.

CRediT authorship contribution statement

Taniya Seth: Conceptualization, Methodology, Data curation, Writing – original draft, Visualization, Investigation. **Pranab K. Muhuri:** Conceptualization, Methodology, Investigation, Supervision, Validation, Writing – review & editing.

Data availability

Data will be made available on request.

Ethics statements

This article does not contain any studies involving human participants performed by any of the authors.

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