Hindawi
Mathematical Problems in Engineering
Volume 2022, Article ID 9299246, 13 pages
https://doi.org/10.1155/2022/9299246

Research Article

A New Interactive Decision Approach with Probabilistic Linguistic Data: An Application in the Academic Sector

K.S. Ravichandran,[1] **R. Krishankumar**,[2] **Sibnath Deb**,[1] **Dragan Pamucar**,[3] **David Paul**,[1] **and Darko Božanić**[4]

[1]*Rajiv Gandhi National Institute of Youth Development, Sriperumbudur, TN, India*
[2]*Department of Computer Science and Engineering, Amrita School of Engineering, Amrita Vishwa Vidyapeetham, Coimbatore, TN, India*
[3]*Department of Logistics, Military Academy, University of Defence in Belgrade, Belgrade, Serbia*
[4]*Military Academy, University of Defence in Belgrade, Belgrade, Serbia*

Correspondence should be addressed to Dragan Pamucar; dragan.pamucar@va.mod.gov.rs

Received 8 December 2021; Revised 14 January 2022; Accepted 22 March 2022; Published 21 April 2022

Academic Editor: Ali Ahmadian

As an innovative generalization to a linguistic term set, the probabilistic variant is gaining abundant attraction in the decision process. However, earlier studies with this variant for decision-making have not adequately explored hesitation in data articulation and interactive ranking. Driven by the claim, in this paper, a new integrated approach is put forward under the probabilistic linguistic context, which attempts to address the claims by presenting a regret/rejoice technique and an interactive WASPAS algorithm for determining the significance of factors and personalized ranking of alternatives. To test the usefulness of the approach, the online course prioritization problem based on empirical data is exemplified, and a comparison demonstrates the benefits and limitations of the proposed work.

1. Introduction

Decision-making under uncertainty is an interesting and complex problem in day-to-day life [1]. Zadeh [2] introduced the concept of linguistic decision-making that was further ameliorated by the work of Herrera et al. [3]. Rodriguez identified that the linguistic term set (LTS) could not accept more than one instance at a given point in time. To resolve the issue, hesitant fuzzy linguistic information (HFLI) [4] was put forward, which embedded the idea of hesitation and allowed more than one instance as preference information. Driven by this feature, many researchers used HFLI for decision-making [5]. Pang et al. [6] identified that though HFLI allowed multiple information, the confidence associated with each element is either ignored or assumed to be the same. A probabilistic linguistic term set (PLTS) was introduced to handle the issue.

PLTS can accept more than one term and associate occurrence probability to each term. This setting gained a lot of attention in the decision-making context in both in theoretical (such as operational laws/aggregation functions [7–13]; ranking [14–19]; measures [20–22]) and the application perspectives [23–29]. Two popular reviews dealing with the applicability of PLTS in decision-making [30] and aggregation operators in the PLTS context [31] give a holistic view of the core importance of the structure for the decision process.

Based on these two reviews, specific challenges can be identified, as follows:

(i) consideration of views from a large population that is heterogeneous is challenging to manage,

(ii) hesitation during opinion sharing is not adequately captured during weight estimation,

(iii) personalized prioritization based on personal choices on alternatives is lacking, along with the idea of capturing interaction among factors.

These challenges motivated the present study, and the following contributions are henceforth made:

(i) PLTS is used to transform the Likert-scale rating from multiple participants to a holistic decision matrix for prioritization of alternatives,
(ii) the regret/rejoice approach is put forward to effectively capture hesitation under the PLTS context; weights of the rating personnel are considered during factor significance calculation,
(iii) a new interactive algorithm with the WASPAS (weighted aggregated sum product assessment) technique as the base formulation is developed to consider personal choices on alternatives and the nature of factors.

These contributions add value to the PLTS-based decision-making and aid in rational selection. Further organization of the paper is as follows. First, literature relating to regret theory and WASPAS are presented in Section 2, tracked by the methodology in Section 3, which covers the core aspect of the paper by detailing step-wise the methods for significance calculation and prioritization. An empirical case example is exemplified in Section 4 to clarify the usefulness of the developed interactive approach. Comparison with other models is also presented to showcase the efficacy and shortcomings of the work. Finally, concluding remarks with future research scope are provided in Section 5.

2. Literature Review

2.1. Regret Theory. Regret theory (RT) is a concept adapted from psychology into decision-making that deals with a clear understanding of the mindset of an expert upon choosing a candidate over another [32]. This idea resembles the human decision process and is a viable approach for determining the hesitation of experts during the decision process [33]. Some review articles [34–37] on RT are prepared by scholars that infer that the concept (i) is elegant and effective in decision-making; (ii) allows efficient capturing of experts' hesitation; and (iii) promotes methodical determination of weights of factors. Chen et al. [38] used the fuzzy context with axiomatic design and RT for logistic provider evaluation under an omnichannel environment. Wang et al. [39] presented a stock grading model with RT and compared the result with prospect theory in the context of fuzzy interval-neutrosophic probability. Qu et al. [40] gave an extended RT with group satisfaction measure under dual hesitant context for grading shared-bikes for an investment. Xia [41] developed the multiobjective model by adopting the RT idea under the hesitant fuzzy linguistic domain to solve firms' decision problems. Gong et al. [42] gave a cloud model with linguistic structure by extending the RT concept over dual expectation of stock evaluation. Wang et al. [43] developed RT-based TOPSIS (a technique for order of preference by similarity to ideal solution) with interval type-2 data in a three-way decision context. Liu et al. [44] assessed projects for venture capitalists under probabilistic hesitant setting by adopting RT and mathematical model formulated using entropy and water-filling strategy. Ren et al. [45] developed an extension to RT under an intuitionistic fuzzy environment by adopting Canberra distance for solving decision problems of supplier selection for assembly components. Gong et al. [46] performed a portfolio assessment with multiobjective programming by considering the RT formulation and the DEA (data envelopment analysis) approach. Liang et al. [47] solved decision problems in probabilistic interval hesitant fuzzy data by developing an integrated RT-gain/lost dominance approach.

2.2. WASPAS Method. The method's inception is from [48], which linearly combines the weighted sum and product measures. Driven by the simplicity of the method, many researchers used the technique for decision-making. Mardani et al. [49] prepared a detailed review on WASPAS showcasing the method's usefulness in the decision process. Mishra et al. [50] evaluated green suppliers in an industry by extending WASPAS with exponential divergence concept with hesitant fuzzy data. Tus and Adali [51] prepared the CRITIC-WASPAS approach as an integrated framework for software evaluation in firms. Pamucar et al. [52] gave a new extension to WASPAS under neutrosophic context for assessing advisors in the process of transporting hazardous goods. Krishankumar et al. [53] came up with a variance-WASPAS integrated method for green supplier selection in a linguistic environment. Bouchraki et al. [54] provided an integrated AHP-WASPAS with fuzzy numbers for assessing claims of customers concerning drinking water service in a firm. Ilbahar et al. developed a Pythagorean fuzzy WASPAS model for renewable energy selection by considering sustainable factors. Krishankumar et al. [55] ranked risk management strategies in the construction sector by proposing a combined framework with variance and WASPAS technique under a double hierarchy setting. Pamucar et al. [56] selected suitable transport modes for reaching airports in Istanbul by preparing a model with fuzzy numbers, a level-based weight assessment technique, and WASPAS. Simic et al. [57] ranked last-mile travel modes of goods by presenting WASPAS under picture fuzzy context. Ali et al. [58] came up with a new framework under an uncertain linguistic setting with arithmetic operations, fusion functions, entropy, and the WASPAS technique for selecting suppliers in a firm. Osintsev et al. [59] assessed compression methods for aerial images by gathering linguistic ratings and adopting neutrosophic WASPAS algorithm. Bozanic et al. [60] prepared a new extension of WASPAS and AHP approaches to ordered fuzzy values for rationally ranking improvement projects.

2.3. Insights from the Review. Based on the previously prepared previously review, it is clear that PLTS is a sophisticated preference structure that can associate confidence levels to terms and aid in heterogeneous data transformation into holistic data forms. Further, determining significance values by properly considering hesitation is crucial in rational decision-making. Finally, the idea of personalized ordering with appropriate consideration to the nature of criteria is key for effective decision-making. The insights are in line with the challenges discussed in the study, which are circumvented by the contributions made in this work.

Figure 1 presents the working model of the proposed interactive approach by utilizing PLD. As claimed in [6], PLD is a flexible preference style that can effectively model diverse opinions from heterogeneous candidates/participants. The procedure adopted for converting the rating information into PLD is explained in Section 3. Data on each online course is given by a diverse set of participants with a different count, background, expertise, demography, and so on. PLTS is a flexible structure adopted to transform the various data into a holistic data matrix to prioritize online professional courses. The data is collected empirically from participants of the short-term online certification course hosted by RGNIYD, an academic institution during the pandemic time. Officials who hosted the certification program acted as experts and offered their opinion on each factor considered for rating the courses. By using the regret/rejoice technique, the significance values of elements are calculated. Later, the data matrix and the significance vector are used by the interactive WASPAS algorithm for the prioritization of online courses given job opportunities for Indian youths. The officials collect personal choices on each course as a choice vector. The nature of factors is also being considered in this interactive WASPAS algorithm for rational prioritization of courses.

3. Methodology

3.1. Preliminaries. The authors provide some basic concepts related to LTS, HFLTS, and PLTS.

Definition 1. Reference [3]. Let $TS = \{s_z | z = 0, 1, \ldots, q\}$ be an LTS with s_0 and s_q as the initial and final objects with v being a positive integer. The features of S are as follows:

If

$$\begin{aligned} &za > zb \text{ then } s_{za} > s_{zb}, \\ &neg(s_{za}) = s_{zb}, \end{aligned} \tag{1}$$

where

$$za + zb = q. \tag{2}$$

Definition 2 [4]. Let TS be as before. Then, an HFLTS is given by

$$D_F = \{a, h_{D_F}(a) | a \in A\}, \tag{3}$$

where

$$h_{D_F}(a) = h(a) = \{s_z^k | k = 1, 2, \ldots, \#h(a)\}. \tag{4}$$

Definition 3 [6]. Let TS be as before. Then, PLTS is given by

$$D(p) = \left\{ D^k(p^k) | D^k \in TS, \ 0 \leq p^k \leq 1, \ \sum_k p^k \leq 1, \ k = 1, 2, \ldots, \#D(p) \right\}, \tag{5}$$

where $D^k(p^k)$ is the k^{th} instance with p^k being the occurrence probability that is associated with the term D^k and $\#D(p)$ refers to the number of instances.

Note 1. $d_i = \{(s_z^k)_i (p_i^k)\}$ is the probabilistic linguistic element (or) probabilistic linguistic data (PLE/PLD) and many such elements constitute the PLTS. Terms have the following semantics:

$$\left\{ \begin{array}{c} s_o = \text{none}, \\ s_1 = \text{extremely low}, \\ s_2 = \text{very low}, \\ s_2 = \text{low}, \\ s_4 = \text{moderate}, \\ s_5 = \text{high}, \\ s_6 = \text{very high}, \\ s_7 = \text{extremely high}. \end{array} \right\}. \tag{6}$$

Definition 4. Reference [21]. Two PLEs d_1 and d_2 considered. Then, the operations are given by

$$\begin{aligned} d_1 \oplus d_2 &= f^{-1}(f(d_1) + f(d_2)), \\ d_1 \oplus d_2 &= f^{-1}(f(d_1) \times f(d_2)), \end{aligned} \tag{7}$$

where f and f^{-1} are obtained from [21]

$$f\colon \tau = \frac{z}{4q} + 0.5, \tag{8}$$

and

$$f^{-1}\colon s_z = s_{(2\tau - 1) \times 2q}. \tag{9}$$

3.2. Data Transformation. This section focuses on converting Likert scale ratings from a heterogeneous set of participants into holistic data for decision-making. PLTS is a suitable structure for supporting this conversion process. Occurrence probability values are associated as confidence values to the different rating terms that give an overview of all the participants and their rating for a particular instance.

The present study considered four professional courses for short-term certification programs conducted online during 2020 (pandemic time). The participant count was

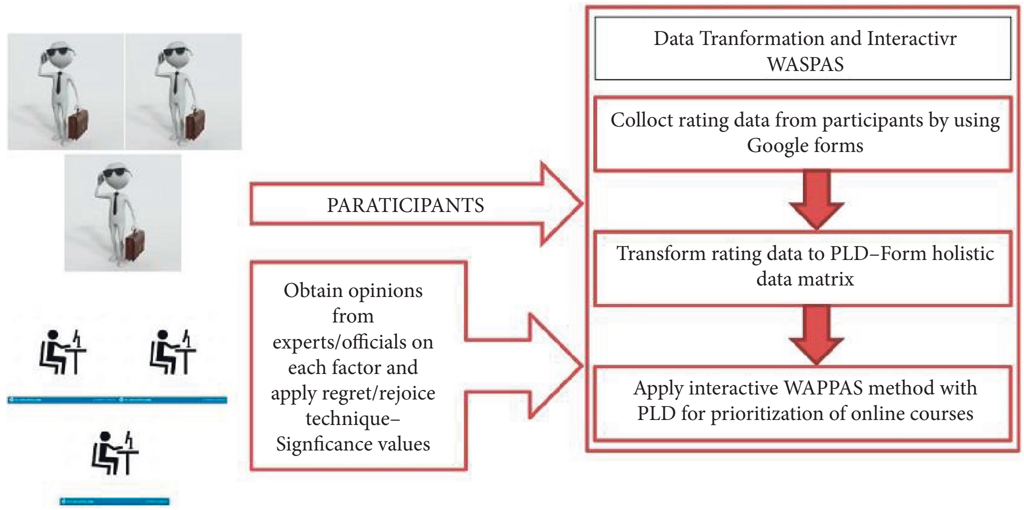

Figure 1: Working model for online professional course selection with PLD.

diverse for each course, and a normal rating was insufficient to grasp the data correctly. Thus, the rating information is transformed to PLD. Proper consideration is given to the diverse participants pertaining to each course by doing the transformation. As a simple walkthrough example, suppose there are two courses, namely, course A and course B, with participants as three and five, respectively, for each course. Rating information is obtained as A(1) = s_4, A(2) = s_3, and A(3) = s_4; B(1) = s_3, B(2) = s_3, B(3) = s_3, B(4) = s_2, and B(5) = s_5. It must be noted that A(1) to A(3) denotes Likert scale rating from three students on course A. Similarly, B(1) to B(5) denotes Likert scale rating from five students on course B. PLEs with respect to course A based on the rating information from three students are calculated as follows:

$$A = \left\{ \begin{array}{c} s_4\left(\dfrac{2}{3}\right) \\ \\ s_3\left(\dfrac{1}{3}\right) \end{array} \right\} = \left\{ \begin{array}{c} s_4(0.67) \\ s_3(0.33) \end{array} \right\},$$
$$B = \left\{ \begin{array}{c} s_3\left(\dfrac{3}{5}\right) \\ \\ s_2\left(\dfrac{1}{5}\right) \\ \\ s_5\left(\dfrac{1}{5}\right) \end{array} \right\} = \left\{ \begin{array}{c} s_3(0.6) \\ s_2(0.2) \\ s_5(0.2) \end{array} \right\}. \tag{10}$$

For course A, the factor 2/3 for s_4 is obtained since two students out of three rated course A as s_4. On the other hand, for course B, a factor of 1/5 is obtained for s_2 since one student rated course B as s_2 out of five students. Similarly, other values can be determined. This mechanism is adopted to transform the input data matrix for ranking online professional courses within the perspective of job opportunities for Indian youths. It must be noted that the instances chosen for the study depend on the expert. For the present study, two cases in high probability are chosen.

3.3. Significance Calculation: Regret/Rejoice Technique. The factors considered for evaluating online courses are competing with one another and pose unbiased or heterogeneous importance. Kao [56] stated that this needs to be methodically determined to avoid subjectivity and inaccuracies from direct elicitation. Popularly, weights are determined either with partial information or unknown information. Programming models are used for partial context, and methods such as entropy [20], analytical methods [62–64], variance [53], and so on are used for unknown context. Though these methods estimate weights, hesitation during opinion sharing is not adequately captured, and the regret factor incurred by the personnel during the decision process is not properly realized. The regret/rejoice technique is put forward under the PLTS context to mitigate the issue. Regret theory [32] is an exciting concept that deals with the psychological aspect and demonstrates the behavior based on a particular choice made by the expert. The technique that evolves from the theory (i) is simple and elegant, (ii) effectively represents the hesitation of experts, and (iii) captures the regret factor incurred by an expert during the decision process. From the review, it is clear that the technique is suitable for the significance determination of factors.

Inspired by the claims, steps for calculation of significance of factors are presented as follows:

Step 1. Experts share their opinions on each factor as a PLE. g vectors of $1 \times y$ order are obtained.

Step 2. Neumann utility function is applied to the score measures of PLEs by using (5) and (6). Neumann values are determined for each opinion value from the expert leading to $g \times y$ values.

$$Sd_{lj} = \sum_k \left(z_{lj}^k \times p_{lj}^k \right), \tag{11}$$

$$UF_j = \sum_{l=1}^{g} v\left(Sd_{lj}\right) + R\left(v\left(Sd_{lj}\right)\right) - v\left(\widetilde{Sd_{lj}}\right), \tag{12}$$

where $v(Sd_{lj}) = (Sd_{lj})^{\eta}$ is the von-Neumann function, $R(v(Sd_{lj})) = 1 - e^{-\beta \times v(Sd_{lj})}$ is the regret function and

$$v\left(\widetilde{Sd_{lj}}\right) = \max_{j \in \text{Benefit}}\left(v\left(Sd_{lj}\right)\right) \text{or} \min_{j \in \text{Cost}}\left(v\left(Sd_{lj}\right)\right). \tag{13}$$

Here, η is the power value, and β is the risk aversion value. Both are considered as 0.50 in this study.

Step 3. Normalize the values from the utility function by using (7) to get the significance vector for the factors. Values from Step 2 are considered as input to determine the significance values.

$$Sf_j = \frac{UF_j}{\sum_j UF_j}, \tag{14}$$

where Sf_j is in the range 0 to 1, with the sum being unity, referred to as the significance value.

3.4. Ranking Alternatives: WASPAS Method. The focus of the section is to present an approach for ranking alternatives based on the set of criteria. As discussed earlier, criteria are heterogeneous and pose biased significance. Therefore, the calculated significance vector from the previous section is utilized here, along with the preference data.

Based on the review previously made, it is clear that WASPAS [48] (i) is simple and elegant; (ii) popularly used in decision-making, and (iii) works using sum/product functions as base formulation. It can be noted that the WASPAS method does not consider the nature of criteria and cannot accept the personal choices of experts during the ranking process. Motivated by the issue, in this section, an interactive extension of WASPAS is put forward, and the stepwise formulation is given as follows.

Step 1. Based on the participants rating, a holistic PLTS data matrix is formed of $x \times y$ order by adopting the procedure given in Section 3.2. Here x denotes the number of professional courses (alternatives), and y represents the number of factors.

Step 2. Apply transformation functions given in (15) to effectively accommodate the nature of factors (criteria) in the rank estimation.

$$d_{ij} = \begin{cases} d_{ij} = d_{ij} \text{ for } j \in \text{ benefit}, \\ d_{ij} = d_{ij}^c \text{ for } j \in \text{ cost}, \end{cases} \tag{15}$$

where $d_{ij}^c = \left\{ s_{q-z_{ij}}^k \left(1 - p_{ij}^k\right) \right\}$ is the complement of d_{ij}. Ideally, the probability values are normalized to retain the property of a PLE. Here q is as denoted in Definition 1.

Step 3. Determine each alternative's weighted sum and product values based on the significance vector and holistic data matrix. Equations (9) and (10) are applied for this purpose.

$$AF_i = \sum_{j=1}^{y} Sf_j \times \left(\sum_k \left(po_i \times \left(\frac{z_{ij}^k \times p_{ij}^k}{\sum_j \left(z_{ij}^k \times p_{ij}^k \right)} \right) \right) \right), \tag{16}$$

$$PF_i = \prod_{j=1}^{y} \left(\left(\sum_k \left(po_i \times \left(\frac{z_{ij}^k \times p_{ij}^k}{\sum_j \left(z_{ij}^k \times p_{ij}^k \right)} \right) \right) \right) \right)^{Sf_j}, \tag{17}$$

where po_i is the personal opinion on alternative i in the unit interval with $\sum_i po_i$ as unity, po_i is a vector of $1 \times x$ order, Sf_j is the significance of factor j, z_{ij}^k is the subscript of the linguistic term in the k^{th} instance for i^{th} professional course rated based on j^{th} factor, p_{ij}^k is the occurrence probability value in the k^{th} instance for i^{th} professional course rated based on j^{th} factor, and AF_i and PF_i are the weighted sum and weighted product values associated with each alternative.

Equations (9) and (10) yield two vectors each of order $1 \times x$, and Sf_j is the significance value of the factor j calculated by applying (14). po_i is another parameter that denotes the personal opinion on an alternative i given by the experts.

It must be noted that when instances of the PLEs are not equal, the procedure mentioned in Definition 6 of [6] is adopted, which makes the instances in the PLEs equal.

Step 4. Calculate the net rank TR_i of each alternative i by adopting the idea of a linear combination of weighted sum and weighted product determined from (9) and (10). Equation (18) is used for the calculation that yields a rank vector of order $1 \times x$.

$$TR_i = \theta \times AF_i + (1 - \theta) \times PF_i, \tag{18}$$

where θ is the strategy measure between 0 and 1.

It must be noted that (18) yields a vector of $1 \times x$ order that contains the rank values of each professional certification course that is considered in the case example. By increasing the strategy values stepwise from 0.1 to 0.9, nine vectors of $1 \times x$ can be obtained from (18). Arrange the values obtained from (18) in the descending order for forming the ordering of alternatives.

4. Case Example: Online Professional Course Selection

This section attempts to exemplify the applicability of the research model. For this, a case example with empirical data from participants is adopted to select suitable online courses for Indian youths focused on job creation for the youth population with an IT background. Four online courses, namely, data science, machine learning, cyber security, and cloud computing were conducted as short-term certifications in RGNIYD, an academic institution. Youths with fair IT background attended the program, and it accounted for 69, 164, 64, and 103, respectively. Out of these, participants who volunteered for data collection were 47, 110, 44, and 83, respectively. It can be seen that the population size is heterogeneous for each online course. To better formulate the data, PLTS is adopted. During the pandemic, these courses were hosted online for the betterment of youths. Resource personnel from the institute of national importance were invited to deliver lectures and hands-on training to the participants.

To further understand the efficacy of these courses in terms of job creation for youths, we invited volunteers to participate in a semistructured questionnaire created using Google forms and circulated online for data collection. The study aimed to rank online courses as per the perception of youth. Factors utilized in the study for rating online courses are the usefulness of the course, job creation from the course, resource personnel content knowledge, expected prerequisite/preparation of the course, stress due to pandemic, and connectivity issues. Based on the literature [65–67] and intuition, these factors are finalized for the study. The last three factors are cost type, and the other factors are benefit type.

For the sake of implementation, authors refer to online courses (cyber security, machine learning, data science, and cloud computing) as CC_1, CC_2, CC_3, and CC_4; factors as FC_1, FC_2, FC_3, FC_4, FC_5, and FC_6; course organizers as CO_1, CO_2, and CO_3. The last three factors are of cost type, while the rest are benefit type. Steps for ranking the online courses are given as follows.

Step 1. Consider rating data from each participant on the four online courses based on the six factors. Likert-scale rating is adopted by participants transformed to PLE by adopting the procedure described in Section 3.2.

Table 1 gives the PLEs as a data matrix for the participants' four courses rated on six linguistically (Likert-scale). The transformation procedure presented in Section 3.2 is used for constructing PLEs from the linguistic data. This is crucial because participants for each course are heterogeneous in terms of count, demography, and so on. The authors considered the top two linguistic terms based on the associated occurrence probability values to build the decision matrix.

Step 2. Officials/organizers of the course (online) provide their rating on the factors that helps in determining the significance of the elements (Table 2). The procedure developed in Section 3.3 is used for this purpose.

The procedure put forward in Section 3.3 is applied to determine the utility values of factors by considering regret/rejoice factors and von-Neumann values (as shown in Figure 2). $v(\widetilde{Sd_{lj}})$ is determined as 2.025, 2.023, 2.098, 1.643, 1.265, and 1.732. Equations (6) and (7) yield the significance values of factors as 0.097, 0.230, 0.090, 0.203.0.170, and 0.210, respectively.

Step 3. With the help of data from Step 1 and vector from Step 2, online courses are ranked by adopting the algorithm proposed in Section 3.4. From the data transformation procedure, the heterogeneous participants' data of each course is holistically transformed into a data matrix of order 4×6. Significance value is a vector of order 1×6.

Personal Opinion. po_i is considered for each course as 0.25, 0.20, 0.35, and 0.20, respectively. From Table 3, the parameter values associated with the improved WASPAS for each online professional course are obtained. The TR_i values indicate the ordering of courses as $CC_3 \succ CC_1 \succ CC_4 \succcurlyeq CC_2$, which infers that the data science course is considered most suited for job opportunities for Indian youths, followed by cyber security, machine learning, and cloud computing. In particular, machine learning and cloud computing are equally preferred by Indian youths in terms of job opportunities in organizations.

Step 4. Conduct sensitivity analysis with significance and strategy values of factors and experts by altering values systematically by shift operations.

Sensitivity measure is investigated in both inter/intracontext by varying the significance of factors through shift operations and periodically increasing step size of strategy values. In the intercontext, the effect of new sets of significance vectors on rank values is determined, and in the intracontext, the impact of strategy values on rank values is determined. Figures 3(a) to 3(f) show the effect of both the values (alteration of weights (inter) and alteration of strategy values (intra) on the ordering of the online professional courses. Six bar graphs are depicted for six weight sets (obtained by shift operation of significance values), and within each graph, strategy values are altered from 0.1 to 0.9. Rank values of each course is plotted as the bar. It can be seen that the Indian youths highly prefer data science in terms of job opportunities in organizations. Courses such as machine learning and cloud computing are equally considered in their respective ranking regarding job opportunities for the youth population. The empirical case study conducted by RGNIYD, an academic institute, serves as a pilot study in effectively understanding the importance of online training (teaching/learning) during pandemic situations and the courses that fetch job opportunities to Indian youths based on their data. The inter/intrasensitivity analysis shows that the proposed framework is robust even after adequate alterations are incorporated.

4.1. Comparison Study. The authors attempt to showcase the efficacy of the proposed work by comparing the model with a close counterpart method [48]. From the sensitivity graph shown in Figure 3, it is clear that the proposed work is highly robust even after alterations to factor significance, and

Table 1: Linguistic data transformed to PLE for decision-making.

Factors	Professional online courses			
	CC_1	CC_2	CC_3	CC_4
FC_1	$\{s_5(0.5), s_4(0.44)\}$	$\{s_4(0.46), s_6(0.36)\}$	$\{s_5(0.5), s_2(0.5)\}$	$\{s_4(0.44), s_3(0.56)\}$
FC_2	$\{s_5(0.45), s_3(0.4)\}$	$\{s_4(0.66), s_5(0.3)\}$	$\{s_6(0.52), s_3(0.4)\}$	$\{s_2(0.35), s_3(0.47)\}$
FC_3	$\{s_3(0.6), s_5(0.4)\}$	$\{s_6(0.55), s_4(0.4)\}$	$\{s_6(0.46), s_4(0.52)\}$	$\{s_5(0.54), s_6(0.43)\}$
FC_4	$\{s_5(0.6), s_2(0.33)\}$	$\{s_4(0.44), s_3(0.33)\}$	$\{s_3(0.63), s_4(0.33)\}$	$\{s_5(0.44), s_3(0.33)\}$
FC_5	$\{s_2(0.25), s_3(0.27)\}$	$\{s_3(0.6), s_4(0.4)\}$	$\{s_5(0.55), s_6(0.33)\}$	$\{s_4(0.62), s_2(0.28)\}$
FC_6	$\{s_6(0.5), s_4(0.5)\}$	$\{s_6(0.35), s_5(0.6)\}$	$\{s_3(0.42), s_2(0.25)\}$	$\{s_3(0.52), s_4(0.44)\}$

Table 2: Opinions for determining factors' significance.

Factors	Officials/organizers		
	CO_1	CO_2	CO_3
FC_1	$\{s_3(0.45), s_4(0.44)\}$	$\{s_4(0.4), s_5(0.5)\}$	$\{s_3(0.6), s_5(0.3)\}$
FC_2	$\{s_5(0.5), s_4(0.4)\}$	$\{s_5(0.6), s_3(0.25)\}$	$\{s_4(0.45), s_5(0.4)\}$
FC_3	$\{s_4(0.4), s_3(0.5)\}$	$\{s_4(0.35), s_6(0.5)\}$	$\{s_4(0.4), s_3(0.6)\}$
FC_4	$\{s_2(0.55), s_4(0.4)\}$	$\{s_5(0.35), s_6(0.4)\}$	$\{s_4(0.45), s_2(0.55)\}$
FC_5	$\{s_3(0.3), s_2(0.35)\}$	$\{s_5(0.4), s_4(0.45)\}$	$\{s_4(0.5), s_5(0.5)\}$
FC_6	$\{s_3(0.6), s_4(0.3)\}$	$\{s_5(0.5), s_4(0.45)\}$	$\{s_5(0.6), s_2(0.4)\}$

Table 3: Rank values associated with each online professional course.

Online courses	Parameters of interactive WASPAS algorithm		
	AF_i	PF_i	TR_i
CC_1	0.066523	0.062433	0.064478
CC_2	0.048126	0.04509	0.046608
CC_3	0.090113	0.083139	0.086626
CC_4	0.047729	0.045634	0.046891

strategy values are done adequately. To further realize the efficacy of the work, the model in [53] is compared with the proposed work. Table 4 gives the summarized view of the theoretical benefits of the proposed work over [53]. Besides, authors also compare the proposed work with extant models, namely, [13, 17] and [23], which actively use PLTS in their framework for attaining rational decisions. Finally, data from the case example are provided to these models, and the courses are ranked, and they are shown in Table 5.

Table 5 and Figure 4 show that the proposed model produces a unique ranking order of professional courses. It can be intuitively inferred owing to the proposed model's ability to consider the nature of factors during the ranking of courses (alternatives) and capture experts' personal opinions during ranking, which provides a sense of personalization and is lacking in existing models. Apart from this, specific theoretical merits of the framework are listed below. Based on the briefing in Table 4, it is inferred that the proposed work is novel and innovative. To further detail the claim, specific points are presented as follows:

(i) PLD is a sophisticated structure that allows for the elegant transformation of rating data from multiple heterogeneous candidates/users. Furthermore, the structure ensures data without loss of generality.

(ii) Driven by the inference from Kao [61], weights are rationally determined by considering risk attitudes and the nature of factors, which is lacking in the close counterpart approach.

(iii) Unlike the framework [53], the ranking algorithm in the proposed work considers the nature of factors and personal choices to provide an interactive, personalized variant of WASPAS with PLD.

O The nature of factors, which is a potential parameter in the decision process, is considered both in weight assessment and ranking, lacking in [53].

O Also, the new formulation allows experts/agents to share their personal opinion on each alternative option (as a vector) that acts as potential information in influencing the ordering of options.

Statistically, the comparison is further extended to realize the superiority of the proposed work. For this purpose, 300 matrices are generated that are used in the simulation experiment. These matrices are of the same dimension as the data in the case example. They are given as input to both the proposed models [53]. Rank vectors are estimated via the algorithm provided in each model. It can be seen that each algorithm obtains 300 vectors of 1×4. Statistical variance is calculated for each vector, so 300 values are obtained, which are plotted in Figure 5. The graph shows that the proposed model can better discriminate alternatives (online courses here) by producing broader vectors than its close counterpart. The graph shows that the proposed model has about six times better discrimination than the counterpart approach. Besides the test for uniqueness of the proposed model put forward in Figure 4, the uniqueness measure is also determined for the 300 orders yielded by the proposed model from the simulation experiment. Spearman rank correlation is applied for the rank values produced by the proposed and counterpart approach. It can be inferred that due to consideration of personal choices, the proposed model produces an order that is unique compared to its close counterpart with an average uniqueness score of 0.7807 for the 300 simulated matrices (Figure 6).

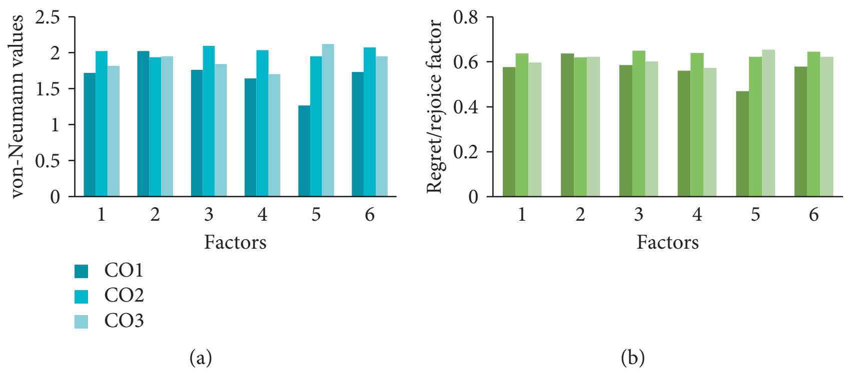

Figure 2: (a) von-Neumann values and (b) regret/rejoice values.

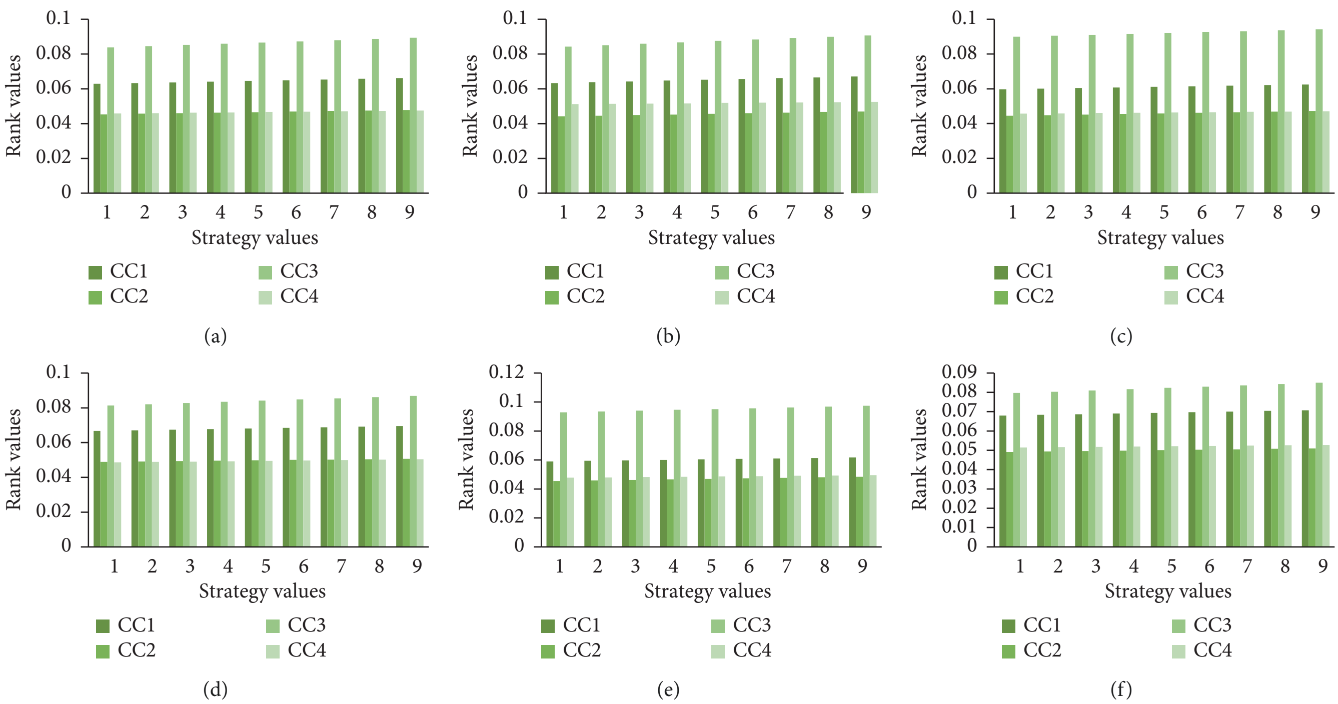

Figure 3: Sensitivity measure of factors' significance: (a) to (f) is set 1 to set 6 (X axis 1 to 9 indicate strategy values from 0.1 to 0.9, resp., with step size 0.1).

In a nutshell, the proposed model is analyzed from both the theoretical and statistical perspective to effectively understand the superiority of the model that is put forth in the present study. It is clear that (i) the model adds value to the PLTS-based decision-making by putting forward a novel framework, whose usefulness is demonstrated by using real case example of professional online course evaluation by collecting empirical data from RGNIYD, an academic institution in India; (ii) later, the test for uniqueness (Figures 4 and 6) shows that the proposed model produces an unique order of alternatives (online courses), which is intuitively backed by the novelty in the formulation of the model that allows consideration of personal choices; and (iii) finally, the test for discriminative power (Figure 5) also reveals that the proposed model produces broader and sensible rank values that aid in better discrimination of alternatives (online courses) for rational decision-making.

Table 4: Summary of characteristics: proposed and other models.

Context	Proposed work	[53]
Data	PLD	PLD
Weights of factors	Calculated methodically	Calculated methodically
Regret attitude characterization	Done, regret/rejoice factor	Not done
Nature of factors	Considered, both during weight assessment and ranking	Not considered
Personal choices of experts	Considered during ranking	Not considered

Table 5: Order of professional courses obtained from PLTS models: proposed versus others.

Course	Proposed	Reference [48] (0.2)	[13]	[17]	[23]
CC_1	2	3	2	3	3
CC_2	4	1	1	1	1
CC_3	1	2	3	2	2
CC_4	3	4	4	4	4

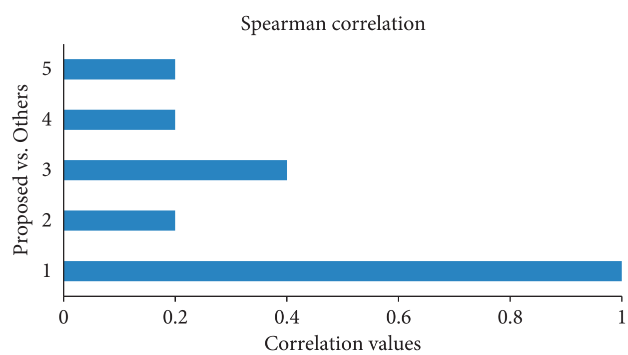

Figure 4: Test of uniqueness in ordering.

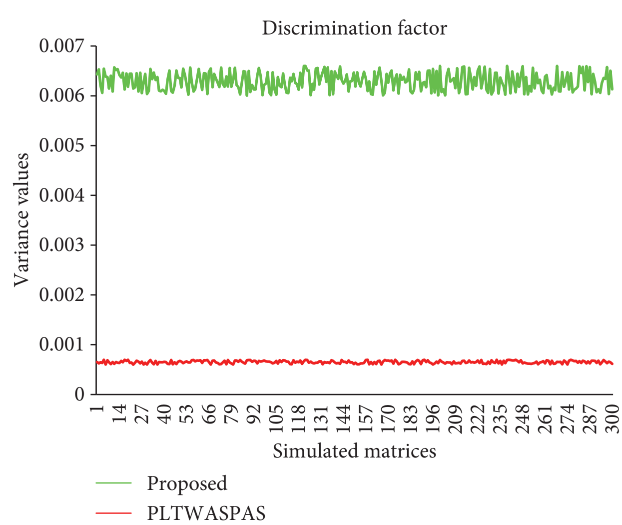

Figure 5: Broadness measure for realizing discrimination factor.

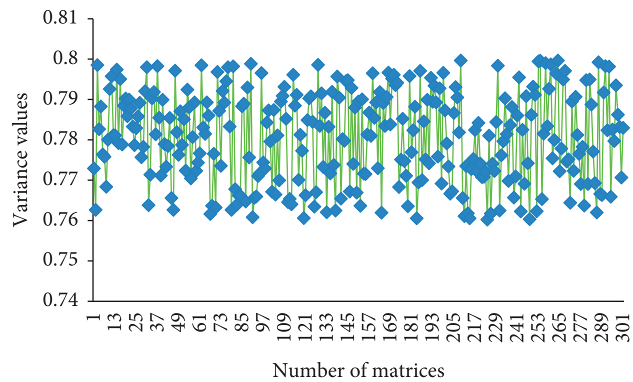

Figure 6: Consistency measure through Spearman correlation.

Table 6: Symbols, semantics, and the respective values.

Symbol	Meaning and value
s_z	Linguistic term with subscript z that can have values as $0, 1, \ldots, q$. q is 6
$d_i = \{(s_z^k)_i (p_i^k)\}$	Probabilistic linguistic element/data with s_z^k as the k^{th} linguistic term and p_z^k as the probability value associated with the k^{th} linguistic term
k	Index for the instance that can take values as $1, 2, \ldots, \#D(p)$
Sd_{lj}	Score measure associated with l^{th} expert and j^{th} factor
Sf_j	Weight/importance associated with factor j. Values are in the range 0 to 1
j	Index associated with the factors
i	Index associated with the alternatives (online courses)
l	Index associated with the experts
g	Number of experts. g is 3
y	Number of factors. y is 6
x	Number of alternatives. x is 4
z_{ij}^k	Subscript of the k^{th} linguistic term given as rating to rate the alternative i based on factor j
p_{ij}^k	Probability associated with the k^{th} linguistic term that is used for rating the alternative i based on factor j
po_i	Personal opinion associated with alternative i. Values are in the range 0 to1. Here, we considered values as 0.25, 0.20, 0.35, and 0.20, respectively for each online course.
AF_i	Weighted sum of alternative i
PF_i	Weighted product of alternative i
TR_i	Net rank value of alternative i
θ	Strategy value that can have values in the range 0 to 1
η	Power value. Considered as 0.50
β	Risk aversion. Considered as 0.50

5. Conclusion

The present study offers an integrated technique put into a framework for decision-making with PLD. The framework adds value to the research in the field of PLTS. The method in the framework calculates weights/significance of factors rationally by considering the hesitation attitudes of experts/agents. Furthermore, an extension to the WASPAS approach is provided with PLD that enables the method to consider the nature of factors during the ordering and personal choices of alternative options from experts/agents. This personal choice as a vector offers a sense of the personalized ordering of options. The framework's benefits can be theoretically and statistically verified by an empirical case study of professional online course selection during the pandemic time. Comprehensive inter-/intrasensitivity analysis and comparison (with close counterpart) reveal the framework's superiority in robustness and acceptable discrimination level.

Some shortcomings of the study are (i) the importance of experts/agents is not methodically derived, and (ii) consideration of top two linguistic instances with its associated single confidence value to the terms (Likert scales) may cause some information loss in the practical sense. On the other hand, a few implications from the managerial perspectives are (i) the framework can be readily adapted for other decision problems in academics and other fields; (ii) transforming rating data from heterogeneous participants into a holistic data matrix by using the PLTS concept is a flexible way for data representation; (iii) though some loss exists in the data, it may be addressed by extending the framework to complete data zone; (iv) the framework gives educational policymakers to effectively plan courses for youth population so that they gain the state-of-the-art skill and knowledge to become ready of industry; (v) finally, some training with the model is expected to aid policymakers in the decision process.

In the future, authors plan to resolve the previously mentioned shortcomings by presenting algorithms for expert weight assessment and considering complete data zone for decision-making. Further, plans are made to propose an integrated approach in the fuzzy variants, such as orthopair sets [68–70] and interval variants of linguistic forms, such as PLTS [6] and double hierarchy variants [71]. Finally, machine learning concepts can be embedded with decision approaches for solving large-scale decision problems in academic and other contexts.

Appendix

The symbols, their notations, and respective values are provided in Table 6 for clarity to readers.

Data Availability

The data used to support the findings of this study are included within this article. However, the reader may contact the corresponding author for more details on the data.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Authors' Contributions

Each author has participated and contributed sufficiently to take public responsibility for appropriate portions of the content.

References

[1] Z. Ali, T. Mahmood, T. Mahmood, K. Ullah, and Q. Khan, "Einstein geometric aggregation operators using a novel complex interval-valued pythagorean fuzzy setting with application in green supplier chain management," *Reports in Mechanical Engineering*, vol. 2, no. 1, pp. 105–134, 2021.

[2] L. A. Zadeh, "The concept of a linguistic variable and its application to approximate reasoning-I," *Information Sciences*, vol. 8, no. 3, pp. 199–249, 1975.

[3] F. Herrera, E. Herrera-Viedma, and J. L. Verdegay, "A sequential selection process in group decision making with a linguistic assessment approach," *Information Sciences*, vol. 85, no. 4, pp. 223–239, 1995.

[4] Y. Ali, M. Ahmad, M. Ahmad, M. Sabir, and S. A. Shah, "Regional development through energy infrastructure: a comparison and optimization of Iran-Pakistan-India (IPI) & Turkmenistan- Afghanistan-Pakistan-India (TAPI) gas pipelines," *Operational Research in Engineering Sciences: Theory and Applications*, vol. 4, no. 3, pp. 82–106, 2021, https://doi.org/10.31181/oresta091221082a.

[5] T. K. Biswas and M. C. Das, "Selection of the barriers of supply chain management in Indian manufacturing sectors due to COVID-19 impacts," *Operational Research in Engineering Sciences: Theory and Applications*, vol. 3, no. 3, pp. 1–12, 2020.

[6] Q. Pang, H. Wang, and Z. Xu, "Probabilistic linguistic term sets in multi-attribute group decision making," *Information Sciences*, vol. 369, pp. 128–143, 2016.

[7] A. Kobina, D. Liang, and X. He, "Probabilistic linguistic power aggregation operators for multi-criteria group decision making," *Symmetry*, vol. 9, no. 12, pp. 320-321, 2017.

[8] P. Liu and F. Teng, "Some Muirhead mean operators for probabilistic linguistic term sets and their applications to multiple attribute decision-making," *Applied Soft Computing*, vol. 68, pp. 396–431, 2018.

[9] S.-P. Wan, W.-B. Huang Cheng, and J.-Y. Dong, "Interactive multi-criteria group decision-making with probabilistic linguistic information for emergency assistance of COVID-19," *Applied Soft Computing*, vol. 107, no. 169, Article ID 107383, 2021.

[10] S.-P. Wan, W.-C. Zou, J.-Y. Dong, and L. Martínez, "A probabilistic linguistic dominance score method considering individual semantics and psychological behavior of decision makers," *Expert Systems with Applications*, vol. 184, Article ID 115372, 2021.

[11] W. Yu, H. Zhang, and B. Li, "Operators and comparisons of probabilistic linguistic term sets," *International Journal of Intelligent Systems*, vol. 34, no. 7, pp. 1476–1504, 2019.

[12] P. Liu and Y. Li, "Multi-attribute decision making method based on generalized maclaurin symmetric mean aggregation operators for probabilistic linguistic information," *Computers & Industrial Engineering*, vol. 131, pp. 282–294, 2019.

[13] D. S. Pamucar and M. Savin, "Multiple-criteria model for optimal off-road vehicle selection for passenger transportation: BWM-COPRAS model," *Military Technical Courier*, vol. 68, no. 1, pp. 28–64, 2020.

[14] X. Gou, Z. Xu, H. Liao, and F. Herrera, "Probabilistic double hierarchy linguistic term set and its use in designing an improved VIKOR method: the application in smart healthcare," *Journal of the Operational Research Society*, vol. 72, no. 12, pp. 2611–2630, 2020.

[15] P. Liu and F. Teng, "Probabilistic linguistic TODIM method for selecting products through online product reviews," *Information Sciences*, vol. 485, pp. 441–455, 2019.

[16] H. Liao, L. Jiang, Z. Xu, J. Xu, and F. Herrera, "A linear programming method for multiple criteria decision making with probabilistic linguistic information," *Information Sciences*, vol. 415-416, pp. 341–355, 2017.

[17] D. Liang, A. Kobina, and W. Quan, "Grey relational analysis method for probabilistic linguistic multi-criteria group decision-making based on geometric bonferroni mean," *International Journal of Fuzzy Systems*, vol. 20, no. 7, pp. 2234–2244, 2018.

[18] X. Wu, H. Liao, Z. Xu, A. Hafezalkotob, and F. Herrera, "Probabilistic linguistic multimoora: a multicriteria decision making method based on the probabilistic linguistic expectation function and the improved borda rule," *IEEE Transactions on Fuzzy Systems*, vol. 26, no. 6, pp. 3688–3702, 2018.

[19] P. Liu and Y. Li, "The PROMTHEE II method based on probabilistic linguistic information and their application to decision making," *Informatica*, vol. 29, no. 2, pp. 303–320, 2018.

[20] H. Liu, L. Jiang, and Z. Xu, "Entropy measures of probabilistic linguistic term sets," *International Journal of Computational Intelligence Systems*, vol. 11, no. 1, pp. 45–57, 2018.

[21] X. Gou and Z. Xu, "Novel basic operational laws for linguistic terms, hesitant fuzzy linguistic term sets and probabilistic linguistic term sets," *Information Sciences*, vol. 372, pp. 407–427, 2016.

[22] G.-l. Xu, S.-P. Wan, and J.-Y. Dong, "An entropy-based method for probabilistic linguistic group decision making and

its application of selecting car sharing platforms," *Informatica*, vol. 31, no. 3, pp. 621–658, 2020.
[23] R. Sivagami, R. Krishankumar, V. Sangeetha, K. S. Ravichandran, S. Kar, and A. H. Gandomi, "Assessment of cloud vendors using interval-valued probabilistic linguistic information and unknown weights," *International Journal of Intelligent Systems*, vol. 36, no. 8, pp. 3813–3851, 2021.
[24] X. Cheng, J. Gu, and Z. Xu, "Venture capital group decision-making with interaction under probabilistic linguistic environment," *Knowledge-Based Systems*, vol. 140, pp. 82–91, 2018.
[25] X. Wu and H. Liao, "An approach to quality function deployment based on probabilistic linguistic term sets and ORESTE method for multi-expert multi-criteria decision making," *Information Fusion*, vol. 43, pp. 13–26, 2018.
[26] R. Sivagami, K. S. Ravichandran, R. Krishankumar et al., "A scientific decision framework for cloud vendor prioritization under probabilistic linguistic term set context with unknown/partial weight information," *Symmetry*, vol. 11, no. 5, p. 682, 2019.
[27] S. Ramadass, R. Krishankumar, K. S. Ravichandran, H. Liao, S. Kar, and E. Herrera-Viedma, "Evaluation of cloud vendors from probabilistic linguistic information with unknown/partial weight values," *Applied Soft Computing*, vol. 97, Article ID 106801, 2020.
[28] X.-B. Mao, M. Wu, J.-Y. Dong, S.-P. Wan, and Z. Jin, "A new method for probabilistic linguistic multi-attribute group decision making: application to the selection of financial technologies," *Applied Soft Computing*, vol. 77, pp. 155–175, 2019.
[29] S.-P. Wan, J. Yan, and J.-Y. Dong, "Personalized individual semantics based consensus reaching process for large-scale group decision making with probabilistic linguistic preference relations and application to COVID-19 surveillance," *Expert Systems with Applications*, vol. 191, Article ID 116328, 2022.
[30] H. Liao, X. Mi, and Z. Xu, "A survey of decision-making methods with probabilistic linguistic information: bibliometrics, preliminaries, methodologies, applications and future directions," *Fuzzy Optim. Decis. Mak.*, 2019.
[31] X. Mi, H. Liao, X. Wu, and Z. Xu, "Probabilistic linguistic information fusion: a survey on aggregation operators in terms of principles, definitions, classifications, applications, and challenges," *International Journal of Intelligent Systems*, vol. 35, no. 3, pp. 529–556, 2020.
[32] D. E. Bell, "Regret in decision making under uncertainty," *Operations Research*, vol. 30, no. 5, pp. 961–981, 1982.
[33] G. Loomes and R. Sugden, "Regret theory: an alternative theory of rational choice under uncertainty," *The Economic Journal*, vol. 92, no. 368, pp. 805–824, 1982.
[34] D. S. Pamucar and S. R. Dimitrijević, "Multiple-criteria model for optimal anti-tank ground missile weapon system procurement," *Military Technical Courier*, vol. 69, no. 4, pp. 792–827, 2021.
[35] I. Mukhametzyanov, "Specific character of objective methods for determining weights of criteria in MCDM problems: entropy, CRITIC and SD," *Decision Making: Applications in Management and Engineering*, vol. 4, no. 2, pp. 76–105, 2021.
[36] D. K. Kushwaha, D. Panchal, D. Panchal, and A. Sachdeva, "Risk analysis of cutting system under intuitionistic fuzzy environment," *Reports in Mechanical Engineering*, vol. 1, no. 1, pp. 162–173, 2020.
[37] V. Romanuke, "Refinement of acyclic-and-asymmetric payoff aggregates of pure strategy efficient Nash equilibria in finite noncooperative games by maximultimin and superoptimality," *Decision Making: Applications in Management and Engineering*, vol. 4, no. 2, pp. 178–199, 2021.
[38] W. Chen, M. Goh, and Y. Zou, "Logistics provider selection for omni-channel environment with fuzzy axiomatic design and extended regret theory," *Applied Soft Computing*, vol. 71, pp. 353–363, 2018.
[39] Y. Wang, J.-Q. Wang, and T.-L. Wang, "Fuzzy stochastic multi-criteria decision-making methods with interval neutrosophic probability based on regret theory," *Journal of Intelligent and Fuzzy Systems*, vol. 35, no. 2, pp. 2309–2322, 2018.
[40] G. Qu, T. Li, X. Zhao, W. Qu, Q. An, and J. Yan, "Dual hesitant fuzzy stochastic multiple attribute decision making method based on regret theory and group satisfaction degree," *Journal of Intelligent and Fuzzy Systems*, vol. 35, no. 6, pp. 6479–6488, 2018.
[41] M. Xia, "A hesitant fuzzy linguistic multi-criteria decision-making approach based on regret theory," *International Journal of Fuzzy Systems*, vol. 20, no. 7, pp. 2135–2143, 2018.
[42] X. Gong, C. Yu, and Z. Wu, "An extension of regret theory based on probabilistic linguistic cloud sets considering dual expectations: an application for the stock market," *IEEE Access*, vol. 7, pp. 171046–171060, 2019.
[43] T. Wang, H. Li, Y. Qian, B. Huang, and X. Zhou, "A regret-based three-way decision model under interval type-2 fuzzy environment," *IEEE Transactions on Fuzzy Systems*, vol. 30, no. 1, pp. 175–189, 2022.
[44] X. Liu, Z. Wang, S. Zhang, and J. Liu, "Probabilistic hesitant fuzzy multiple attribute decision-making based on regret theory for the evaluation of venture capital projects," *Economic Research-Ekonomska Istraživanja*, vol. 33, no. 1, pp. 672–697, 2020.
[45] H. Ren, Y. Gao, and T. Yang, "A novel regret theory-based decision-making method combined with the intuitionistic fuzzy Canberra distance," *Discrete Dynamics in Nature and Society*, vol. 2020, pp. 1–9, Article ID 8848031, 2020.
[46] X. Gong, C. Yu, L. Min, and Z. Ge, "Regret theory-based fuzzy multi-objective portfolio selection model involving DEA cross-efficiency and higher moments," *Applied Soft Computing*, vol. 100, Article ID 106958, 2021.
[47] W. Liang and Y.-M. Wang, "A probabilistic interval-valued hesitant fuzzy gained and lost dominance score method based on regret theory," *Computers & Industrial Engineering*, vol. 159, Article ID 107532, 2021.
[48] S. Chakraborty and E. K. Zavadskas, "Applications of WASPAS method in manufacturing decision making," *Informatica*, vol. 25, no. 1, pp. 1–20, 2014.
[49] A. Mardani, M. Nilashi, N. Zakuan et al., "A systematic review and meta-Analysis of SWARA and WASPAS methods: theory and applications with recent fuzzy developments," *Applied Soft Computing*, vol. 57, pp. 265–292, 2017.
[50] A. R. Mishra, P. Rani, K. R. Pardasani, and A. Mardani, "A novel hesitant fuzzy WASPAS method for assessment of green supplier problem based on exponential information measures," *Journal of Cleaner Production*, vol. 238, Article ID 117901, 2019.
[51] A. Tuş and E. Aytaç Adalı, "The new combination with CRITIC and WASPAS methods for the time and attendance software selection problem," *Opsearch*, vol. 56, no. 2, pp. 528–538, 2019.
[52] D. Pamučar, S. Sremac, Ž. Stević, G. Ćirović, and D. Tomić, "New multi-criteria LNN WASPAS model for evaluating the work of advisors in the transport of hazardous goods," *Neural Computing & Applications*, vol. 31, no. 9, pp. 5045–5068, 2019.

[53] R. Krishankumar, R. Saranya, R. P. Nethra, K. S. Ravichandran, and S. Kar, “A decision-making framework under probabilistic linguistic term set for multi-criteria group decision-making problem,” *Journal of Intelligent and Fuzzy Systems*, vol. 36, no. 6, pp. 5783–5795, 2019.
[54] F. Bouchraki, A. Berreksi, and S. Hamchaoui, “Evaluating the policy of listening to customer claims in a drinking water utility using fuzzy-AHP approach and WASPAS method,” *Water Policy*, vol. 23, no. 1, pp. 167–186, 2021.
[55] R. Krishankumar, L. S. Subrajaa, K. S. Ravichandran, S. Kar, and A. B. Saeid, “A framework for multi-attribute group decision-making using double hierarchy hesitant fuzzy linguistic term set,” *International Journal of Fuzzy Systems*, vol. 21, pp. 1–14, 2019.
[56] D. Pamucar, M. Deveci, F. Canıtez, and V. Lukovac, “Selecting an airport ground access mode using novel fuzzy LBWA-WASPAS-H decision making model,” *Engineering Applications of Artificial Intelligence*, vol. 93, Article ID 103703, 2020.
[57] V. Simi and D. Lazarevi, “Picture fuzzy WASPAS method for selecting last-mile delivery mode : a case study of Belgrade,” vol. 6, 2021.
[58] J. Ali, Z. Bashir, and T. Rashid, “WASPAS-based decision making methodology with unknown weight information under uncertain evaluations,” *Expert Systems with Applications*, vol. 168, Article ID 114143, 2021.
[59] N. Osintsev, A. Rakhmangulov, and V. Baginova, “Evaluation of logistic flows in green supply chains based on the combined DEMATEL-ANP method,” *Facta Universitatis – Series: Mechanical Engineering*, vol. 19, no. 3, pp. 473–498, 2021.
[60] D. Bozanic, A. Milic, D. Tešic, W. Salabun, and D. Pamucar, “D numbers – FUCOM – fuzzy RAFSI model for selecting the group of construction machines for enabling mobility,” *Facta Universitatis – Series: Mechanical Engineering*, vol. 19, no. 3, pp. 447–471, 2021.
[61] S.-H. Lin, X. Zhao, J. Wu et al., “An evaluation framework for developing green infrastructure by using a new hybrid multiple attribute decision-making model for promoting environmental sustainability,” *Socio-Economic Planning Sciences*, vol. 75, Article ID 100909, 2021.
[62] S. Seker and C. Kahraman, “Socio-economic evaluation model for sustainable solar PV panels using a novel integrated MCDM methodology: a case in Turkey,” *Socio-Economic Planning Sciences*, vol. 77, Article ID 100998, 2021.
[63] G. Büyüközkan, E. Mukul, and E. Kongar, “Health tourism strategy selection via SWOT analysis and integrated hesitant fuzzy linguistic AHP-MABAC approach,” *Socio-Economic Planning Sciences*, vol. 74, Article ID 100929, 2021.
[64] D. M. d. Oliveira Dias, D. R. d. O. Albergarias Lopes, and A. C. Teles, “Will virtual replace classroom teaching? Lessons from virtual classes via zoom in the times of COVID-19,” *Journal of Advances in Education and Philosophy*, vol. 4, no. 5, pp. 208–213, 2020.
[65] A. Rahman, “Using students’ experience to derive effectiveness of COVID-19-lockdown-induced emergency online learning at undergraduate level: evidence from Assam, India,” *Higher Education for the Future*, vol. 8, no. 1, pp. 71–89, 2021.
[66] M. Aggarwal, “Attitudinal Choquet integrals and applications in decision making,” *International Journal of Intelligent Systems*, vol. 33, no. 4, pp. 879–898, 2018.
[67] C. Kao, “Weight determination for consistently ranking alternatives in multiple criteria decision analysis,” *Applied Mathematical Modelling*, vol. 34, no. 7, pp. 1779–1787, 2010.
[68] S. Zeng, M. Shoaib, S. Ali, F. Smarandache, H. Rashmanlou, and F. Mofidnakhaei, “Certain properties of single-valued neutrosophic graph with application in food and agriculture organization,” *International Journal of Computational Intelligence Systems*, vol. 14, no. 1, pp. 1516–1540, 2021.
[69] S. Zeng, N. Zhang, C. Zhang, W. Su, and L.-A. Carlos, “Social network multiple-criteria decision-making approach for evaluating unmanned ground delivery vehicles under the Pythagorean fuzzy environment,” *Technological Forecasting and Social Change*, vol. 175, Article ID 121414, 2022.
[70] S. Zeng, S. Ali, M. K. Mahmood, F. Smarandache, and D. Ahmad, “Decision-making problems under the environment of m-polar diophantine neutrosophic N-soft set,” *C. - Comput. Model. Eng. Sci.*, vol. 129, no. 1, 2021.
[71] X. Gou, P. Xiao, D. Huang, and F. Deng, “Probabilistic double hierarchy linguistic alternative queuing method for real economy development evaluation under the perspective of economic financialization,” *Economic Research-Ekonomska Istraživanja*, pp. 1–60, 2021.