Hindawi
Mathematical Problems in Engineering
Volume 2021, Article ID 9975056, 18 pages
https://doi.org/10.1155/2021/9975056

Research Article

An Extended Prospect Theory for Robot Evaluation and Selection considering Risk Preferences and Interactive Criteria

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Received 10 March 2021; Accepted 3 June 2021; Published 19 June 2021

Academic Editor: Paolo Boscariol

The evaluation and selection process can be regarded as a complex multiple criteria decision analysis (MCDA) problem which involves various interaction relationships among criteria under high uncertain environment. In addition, the decision-makers are always bounded rational in the risk decision-making process. However, the current robot evaluation and selection approach seldom considers the decision-maker's risk preference and interactive criteria under high uncertain environment. Thus, the purpose of this paper is to develop a hybrid MCDA approach for solving the robot evaluation and selection problem. In the proposed framework, the interval type-2 fuzzy set is used to express the uncertain evaluation information provided by decision-makers. Next, the distance measure of interval type-2 fuzzy numbers is developed to determine the fuzzy measure of each criterion. Then, the extended prospect theory based on developed Choquet integral is proposed to evaluate and prioritize the robot by considering the decision-maker's risk preference and interactive criteria. Finally, a case study of robot evaluation and selection in the auto industry is selected to exemplify the application of the proposed framework. After that, comparison and sensitivity studies are conducted to further demonstrate the robustness, effectiveness, and reasonableness of the developed approach.

1. Introduction

In recent years, Industry 4.0 has been used to describe the features of the digitized and automated manufacturing industry [1]. Meanwhile, "Made in China 2025" is the first ten-year action guiding proposed to transform China into a strong manufacturing power [2]. Both of these advanced manufacturing models require various intellectual support, advanced information science, and technology [3]. Robots are regarded as an important style of intellectual device, which can meet the engineering technical requirements of these advanced manufacturing models [2]. In this context, robot evaluation and selection procedures have been a crucial concern and the most challenging problems for manufacturing industries [4].

In the literature, in the robot evaluation and selection process, the application of expert elicitation is one of the most important approaches to depict the uncertainties of robot evaluation and selection. Consequently, some important techniques are used to depict the uncertain evaluation information from various experts. These techniques include triangular fuzzy numbers (TFNs) [5, 6], generalized interval-valued fuzzy numbers (GIFNs) [7], interval 2-tuple linguistic terms set (ITLTS) [8], hesitant 2-tuple linguistic term sets (HTLTS) [9], interval type-2 fuzzy set (IT2FS) [10], interval-valued Pythagorean uncertain linguistic set (IVPFLS) [11], interval-valued intuitionistic hesitant fuzzy set (IVIHFS) [3], and hesitant fuzzy linguistic term sets (HFL) [2]. Among these uncertainty expression methods, the interval type-2 fuzzy set can effectively deal with the intra- and interuncertainty of the evaluation process [12]; thus, the interval type-2 fuzzy set is selected to depict the uncertain evaluation information in this paper.

In general, evaluation and selection of optimal robot for an industrial application is completed by a group of decision-makers from various fields, in which different kinds of factors, such as cost, quality, and functions man-machine interface, should be taken into account [13–15]. Accordingly, the robot evaluation and selection process can be regarded as a multiple criteria decision analysis (MCDA) problem. In such case, many MCDA techniques have been extended to cope with the robot evaluation and selection problem (see, e.g., Vahdani et al. [16], Parameshwaran et al. [14], Xue et al. [9], Gitinavard et al. [17], Liu et al. [11], and Wang et al. [18]). Although these existing MCDA techniques can help to address the robot evaluation and selection problem, they have no capability to model the decision-makers that may be bounded rational when selecting optimal robot [18, 19]. The prospect theory, as a behavior decision-making method, can effectively model the risk preference of decision-maker in uncertain decision-making process. In addition, the prospect theory has been extended to various types of alternative selection problems for modeling the risk preference of decision-maker (Liu and Liu [20], Li et al. [21], Ying et al. [22], Sun et al. [23], Wan et al. [24], and Wang et al. [25]). For instance, in order to determine the most suitable solar water heater, Liu et al. [26] developed the traditional prospect theory with linguistic terms. Munjal and Singh [27] proposed a hybrid network selection method by incorporating the prospect theory with game theory. Dou et al. [28] reported an improved hybrid product personalized design evaluation and selection approach by using the extended prospect theory. Wu et al. [29] combined the prospect theory with triangular fuzzy sets to evaluate and select the suitable renewable power sources. Zhao et al. [30] extended the prospect theory with the best-worst method into the selection of battery energy storage systems. Thus, the prospect theory is utilized to address robot evaluation and selection problem in this paper.

In addition, the robot evaluation and selection process in the practice includes many objective and subjective factors, some of which are affected by each other [2, 8]. Hence, it is very important to take the interactive relationships among these factors into account during the robot selection procedure. In the literature, some methods have been developed to deal with the modeling of interactive criteria. For instance, Wan et al. [31] used the analytic network process (ANP) method to model the interactive relationships among criteria. Liu et al. [32] introduced a hybrid decision-making trial and evaluation laboratory (DEMATEL) method to simulate the internal relationships between criteria. Demirel et al. [33] utilized the Choquet integral to address the interactive criteria modeling problem in the determining process of the optimal location for warehouse. Compared with the ANP and DEMATEL, the Choquet integral not only can take into account the interactive relationships among criteria but also can provide a noncompensatory aggregation procedure in robot evaluation and selection process [34]. Therefore, the Choquet integral is adopted to model the interactive relationships among criteria.

As mentioned above, little attention has been paid to addressing robot selection problem by considering the risk preference of decision-makers and the interactive criteria within high type uncertain environment. Compared with the type-1 fuzzy set, the type-2 fuzzy set is an effective technique to depict high type uncertainty [35]. The prospect theory is suitable to determine the optimal robot considering the decision-maker's risk preference. However, the conventional prospect theory is insufficient to address priority calculation problem with interactive criteria [34]. The Choquet integral is a useful method to construct prioritization approach by considering interaction relationships among criteria. In such case, it is suitable to combine prospect theory with Choquet integral and interval type-2 fuzzy set for solving the robot evaluation and selection problem. Moreover, no research develops prospect theory-based prioritization method by using Choquet integral and interval type-2 fuzzy set for robot evaluation and selection. Therefore, we proposed an extended prospect theory-based prioritization approach to address robot evaluation and selection problem with interactive criteria under interval type-2 fuzzy environment.

As the discussion mentioned above, the summaries of the main contributions of this study to the relevant literature are provided as follows:

(1) A developed hybrid decision-making framework for robot evaluation and selection is constructed. The results of comparison analysis and sensitivity analysis indicate that the proposed approach embodies a few desirable features to address the robot evaluation and selection problem compared with the extant approaches.

(2) The distance measure of interval type-2 fuzzy numbers is introduced to determine the fuzzy measure of each criterion, which not only can provide an objective weight vector for robot evaluation and selection but also can provide a more reasonable result than the weight vector assigned beforehand.

(3) A developed Choquet integral is incorporated into the traditional prospect theory for solving the robot evaluation and selection problem, in which the decision-maker's risk preference and interactive criteria are considered. In addition, the positive and negative reference points are introduced into the traditional prospect theory to determine the optimal robot, which can express the complex risk preference of decision-makers more effectively than the existing methods for robot selection.

The remainder of this paper is organized as follows. In Section 2, the concepts of interval type-2 fuzzy set, prospect theory, and Choquet integral are briefly introduced. Section 3 introduces the specific steps of the solution for robot selection problems under interval type-2 fuzzy environment. In Section 4, an illustrative example is used to demonstrate the application and effectiveness of the proposed method in robot selection problems. In Section 5, the conclusions and future research directions are summarized.

2. Preliminaries

In this section, the basic concepts related to interval type-2 fuzzy set, prospect theory, and Choquet integral are briefly reviewed, which shall be used in the subsequent sections.

2.1. Interval Type-2 Fuzzy Set

Definition 1 (see [36]). A type-2 fuzzy set in the universe of discourse can be expressed by a type-2 membership function, which can be defined as follows:

$$\tilde{\tilde{A}} = \left\{ \left((x,u), \mu_{\tilde{\tilde{A}}}(x,u) \right) \middle| \forall x \in X, \forall u \in J_x \subseteq [0,1] \right\}. \quad (1)$$

$J_x \subseteq [0,1]$ and $0 \le \mu_{\tilde{\tilde{A}}}(x,u) \le 1$ for all admissible x and u. In addition, the type-2 fuzzy set $\tilde{\tilde{A}}$ can also be denoted as follows:

$$\tilde{\tilde{A}} = \int_{x\in\chi} \int_{u\in J_x} u_{\tilde{\tilde{A}}} \frac{(x,u)}{(x,u)}, \quad (2)$$

where the symbol $\int\int$ is union over all admissible x and u. The parameters x and u indicate the primary and secondary variables of the type-2 fuzzy set $\tilde{\tilde{A}}$, respectively.

Definition 2 (see [36, 37]). Let $\tilde{\tilde{A}}$ be a type-2 fuzzy set in the universe of discourse X expressed by the type-2 membership function $\mu_{\tilde{\tilde{A}}}$. If all $\mu_{\tilde{\tilde{A}}}(x,u) = 1$, then $\tilde{\tilde{A}}$ is defined as an interval type-2 fuzzy set (IT2FS). An IT2FS $\tilde{\tilde{A}}$ can be regarded as a special case of the type-2 fuzzy set, and it can be represented as follows:

$$\tilde{\tilde{A}} = \int_{x\in X} \int_{u\in J_x} \frac{1}{(x,u)}. \quad (3)$$

Definition 3 (see [36–38]). In general, the interval type-2 trapezoidal fuzzy number (IT2TrFN) is selected to express the IT2FS. Let $\tilde{\tilde{A}} = \begin{bmatrix} (a_1^L, a_2^L, a_3^L, a_4^L; h_A^L), \\ (a_1^U, a_2^U, a_3^U, a_4^U; h_A^U) \end{bmatrix}$ be an IT2FrFN, which is expressed as $\tilde{\tilde{A}} = \begin{bmatrix} (a_1^L, a_2^L, a_3^L, a_4^L; h_A^L), \\ (a_1^U, a_2^U, a_3^U, a_4^U; h_A^U) \end{bmatrix}$. Based on that, the visual representation of an IT2TrFN is shown in Figure 1.

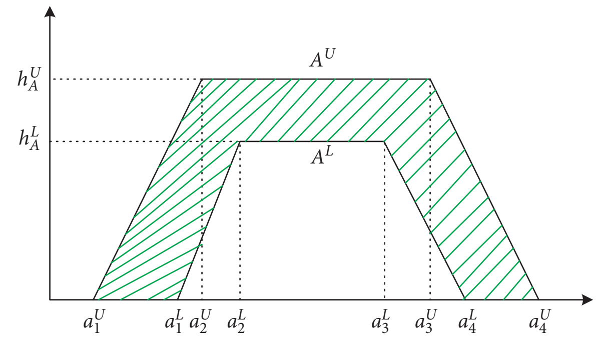

Figure 1: Visual representation of an IT2TrFN.

Definition 4 (see [39]). Assume that $\tilde{\tilde{A}}_1$ and $\tilde{\tilde{A}}_2$ are two IT2TrFNs as shown in the following form: $\tilde{\tilde{A}}_1 = [(a_{11}^L, a_{12}^L, a_{13}^L, a_{14}^L; h_{1A}^L), (a_{11}^U, a_{12}^U, a_{13}^U, a_{14}^U; h_{1A}^U)]$, $\tilde{\tilde{A}}_2 = [(a_{21}^L, a_{22}^L, a_{23}^L, a_{24}^L; h_{2A}^L), (a_{21}^U, a_{22}^U, a_{23}^U, a_{24}^U; h_{2A}^U)]$. Then, the arithmetic operations between $\tilde{\tilde{A}}_1$ and $\tilde{\tilde{A}}_2$ can be defined as follows:

(1) Addition operation

$$\tilde{\tilde{A}}_1 \oplus \tilde{\tilde{A}}_2 = \begin{bmatrix} \left(a_{11}^L + a_{21}^L, a_{12}^L + a_{22}^L, a_{13}^L + a_{23}^L, a_{14}^L + a_{24}^L; \min\{h_{1A}^L, h_{2A}^L\} \right), \\ \left(a_{11}^U + a_{21}^U, a_{12}^U + a_{22}^U, a_{13}^U + a_{23}^U, a_{14}^U + a_{24}^U; \min\{h_{1A}^U, h_{2A}^U\} \right) \end{bmatrix}. \quad (4)$$

(2) Subtraction operation

$$\tilde{\tilde{A}}_1 \ominus \tilde{\tilde{A}}_2 = \begin{bmatrix} \left(a_{11}^L - a_{24}^L, a_{12}^L - a_{23}^L, a_{13}^L - a_{22}^L, a_{14}^L - a_{21}^L; \min\{h_{1A}^L, h_{2A}^L\} \right), \\ \left(a_{11}^U - a_{24}^U, a_{12}^U - a_{23}^U, a_{13}^U - a_{22}^U, a_{14}^U - a_{21}^U; \min\{h_{1A}^U, h_{2A}^U\} \right) \end{bmatrix}. \quad (5)$$

(3) Multiplication operation

$$\tilde{\tilde{A}}_1 \otimes \tilde{\tilde{A}}_2 = \begin{bmatrix} \left(a_{11}^L \cdot a_{21}^L, a_{12}^L \cdot a_{22}^L, a_{13}^L \cdot a_{23}^L, a_{14}^L \cdot a_{24}^L; \min\{h_{1A}^L, h_{2A}^L\} \right), \\ \left(a_{11}^U \cdot a_{21}^U, a_{12}^U \cdot a_{22}^U, a_{13}^U \cdot a_{23}^U, a_{14}^U \cdot a_{24}^U; \min\{h_{1A}^U, h_{2A}^U\} \right) \end{bmatrix}. \quad (6)$$

(4) Multiplication by crisp number operation

$$k \cdot \tilde{\tilde{A}}_1 = \begin{bmatrix} \left(k \cdot a_{11}^L, k \cdot a_{12}^L, k \cdot a_{13}^L, k \cdot a_{14}^L; h_{1A}^L \right), \\ \left(k \cdot a_{11}^U, k \cdot a_{12}^U, k \cdot a_{13}^U, k \cdot a_{14}^U; h_{1A}^U \right) \end{bmatrix}, \quad k > 0. \quad (7)$$

(5) Power operation

$$\tilde{\tilde{A}}_1^{\alpha}=\begin{bmatrix}\left(\left(a_{11}^{L}\right)^{\alpha},\left(a_{12}^{L}\right)^{\alpha},\left(a_{13}^{L}\right)^{\alpha},\left(a_{14}^{L}\right)^{\alpha};h_{1A}^{L}\right),\\ \left(\left(a_{11}^{U}\right)^{\alpha},\left(a_{12}^{U}\right)^{\alpha},\left(a_{13}^{U}\right)^{\alpha},\left(a_{14}^{U}\right)^{\alpha};h_{1A}^{U}\right)\end{bmatrix}. \tag{8}$$

Definition 5 (see [40]). Let $\tilde{\tilde{A}}_1$ and $\tilde{\tilde{A}}_2$ be two IT2TrFNs; then the distance between $\tilde{\tilde{A}}_1$ and $\tilde{\tilde{A}}_2$ can be defined as follows:

$$d\left(\tilde{\tilde{A}}_1,\tilde{\tilde{A}}_2\right)=\left|R_d\left(\tilde{\tilde{A}}_1,\tilde{\tilde{1}}\right)-R_d\left(\tilde{\tilde{A}}_2,\tilde{\tilde{1}}\right)\right|, \tag{9}$$

where $\tilde{\tilde{1}}=[(1,1,1,1;1),(1,1,1,1;1)]$ and

$$\begin{aligned}R_d\left(\tilde{\tilde{A}}_1,\tilde{\tilde{1}}\right)&=\frac{1}{2h_{1A}^{L}\cdot h_{1A}^{U}}\left[h_{1A}^{L}\cdot\left(a_{14}^{U}-a_{13}^{U}-a_{14}^{L}+a_{13}^{L}\right)\right]\\&-\frac{1}{2h_{1A}^{L}\cdot h_{1A}^{U}}\left[h_{1A}^{U}\cdot\left(0.5\left(a_{12}^{L}-a_{11}^{L}-a_{12}^{U}+a_{11}^{U}\right)-\left(a_{14}^{L}-a_{13}^{L}-a_{12}^{L}+a_{11}^{L}\right)\right)\right]\\&+1-a_{14}^{L}-0.5\left(a_{11}^{L}-a_{11}^{U}+a_{14}^{U}-a_{14}^{L}\right).\end{aligned} \tag{10}$$

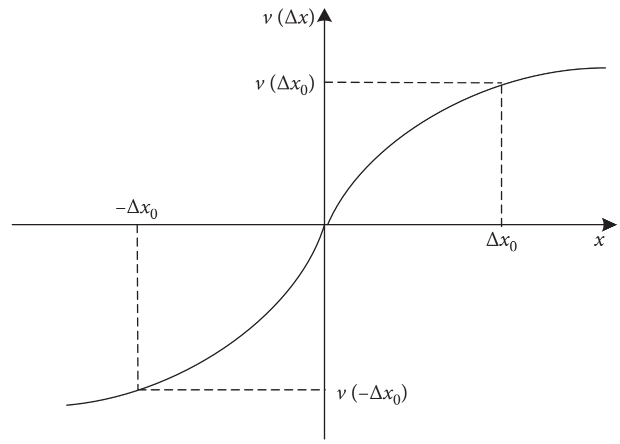

Figure 2: A value function of prospect theory.

2.2. Prospect Theory. The prospect theory was introduced by Kahneman D [41], which can be adopted to model the behavior characteristics of decision-makers within the risk and uncertain context [42]. The prospect theory uses a value function to depict the degree of gains and losses. The value function in prospect theory can be expressed as deviations from the reference point with a convex and concave S-shape for losses and gains, respectively [14], which can be shown in Figure 2.

Based on the value function defined in Figure 2, x is the value of gain or loss relative to the reference point. If $x>0$, it means the gain relative to reference, and if $x<0$, it means the loss relative to reference point. The mathematical expression of the value function in prospect theory is denoted as the following form:

$$v(x)=\begin{cases}x^{\alpha}, & x\geq 0,\\ -\theta(-x)^{\beta}, & x<0,\end{cases} \tag{11}$$

where the parameters α and β are the decision-makers' risk attitude coefficient, which are the convexity and concavity of the value function of prospect theory, respectively, $0<\alpha<1, 0<\beta<1$. The parameter θ indicates the risk loss aversion coefficient of decision-makers, which satisfies $\theta>1$.

2.3. Choquet Integral. The theory of fuzzy measure, primely introduced by [43], is widely used as an information aggregation method for MCDA problems.

Definition 6 (see [14]). Let $X=\{x_1,x_2,\ldots,x_n\}$ be a fixed set; if the fuzzy measure ϕ on X satisfies the following equation, it can be defined as a λ−fuzzy measure.

$$\phi(A\cup B)=\phi(A)+\phi(B)+\lambda\phi(A)\phi(B), \tag{12}$$

where $\lambda\in(-1,\infty)$ $\forall A,B\in F(X)$ and $A\cap B=\varnothing$.

If the set X is a finite set, and $X=\cup_{i=1}^{n}x_i$, then λ−fuzzy measure defined above can be also expressed as follows:

$$\phi(X)=\begin{cases}\dfrac{1}{\lambda}\left[\displaystyle\prod_{i=1}^{n}\left(1+\lambda\phi(x_i)\right)-1\right], & \text{if }\lambda\neq 0,\\ \displaystyle\sum_{i=1}^{n}\phi(x_i), & \text{if }\lambda=0.\end{cases} \tag{13}$$

According to equation (14), the value of parameter λ can be obtained uniquely by considering the boundary condition $\phi(X)=1$ that is equal to solving equation (15).

$$\lambda+1=\prod_{i=1}^{n}\left(1+\lambda\phi(x_i)\right). \tag{14}$$

Definition 7 (see [14, 44]). Assume that ϕ is a fuzzy measure on X, and the function $X=\{x_1,x_2,\ldots,x_n\}$ is a positive, real-valued, and measurable function on set $X=\{x_1,x_2,\ldots,x_n\}$. Then, the discrete Choquet integral can be denoted as follows:

$$\int g\,\mathrm{d}\phi=\sum_{i=1}^{n}g\left(x_{(i)}\right)\left[\phi\left(A_{(i)}\right)-\phi\left(A_{(i-1)}\right)\right], \tag{15}$$

where $g(x_{(i)})$ is a monotonic nondecreased function, then $g(x_{(1)})\geq g(x_{(2)})\cdots\geq g(x_{(n)})\geq 0$, and $A_{(0)}=\varnothing$, $A_{(1)}=\{x_{(1)}\}$, $A_{(2)}=\{x_{(1)},x_{(2)}\},\ldots,A_{(n)}=\{x_{(1)},x_{(2)},\ldots,x_{(n)}\}$.

3. The Extended Prospect Theory for Robot Evaluation and Selection

In this section, we incorporate the extended prospect theory into the performance evaluation and prioritization determination procedures to address the robot evaluation and selection problems with interactive criteria and interval type-2 fuzzy numbers. According to the literature review of current robot evaluation and selection methods mentioned in Section 2, the risk preferences of decision-makers and interactive relationships among criteria are not fully taken into account in the robot selection process. Accordingly, a hybrid robot evaluation and selection approach is proposed by integrating IT2TrFNs, prospect theory, and Choquet integral. In the hybrid framework, the IT2TrFNs are applied to express the uncertain evaluation information from various experts. Next, the weighted arithmetic averaging (WAA) operator is used to aggregate individual evaluation information and construct group evaluation matrix. Then, a distance measure for IT2TrFNs based method is developed for determining fuzzy measure of each criterion. Finally, the extended prospect theory based on Choquet integral and distance measure is introduced to calculate priorities of robots and to select the optimal robot. The proposed evaluation and selection approach consists of three stages, and its algorithm flowchart of the proposed selection approach is provided in Figure 3. These detailed stages of the hybrid framework are presented as follows.

3.1. Stage 1: Obtain Evaluation Information for Each Robot. The scope of this stage is to obtain the evaluation information by the application of expert elicitation. Various types of uncertainties may exist in the robot evaluation and selection problems because of the intra- and interuncertain evaluation information produced by decision-makers [45]. Compared with the type-1 fuzzy set, the type-2 fuzzy set can deal with such uncertainties more effectively [38, 40]. In such cases, the IT2TrFNs are adopted to express the evaluation information from various decision-makers.

Step 1. Construct the evaluation matrix by using linguistic terms.

In this study, we assume that there are m robots $\{a_1, \ldots a_i, \ldots, a_m\}$ satisfying the requirement of the industry, and the set $\{c_1, \ldots, c_j, \ldots, c_n\}$ is the n criteria used to evaluate and select the optimal alternative robot. We assume that a group of experts $e_k\,(k = 1, 2, \ldots, t)$, whose importance weights are $\{\omega^1, \ldots, \omega^k, \ldots, \omega^t\}$, is invited to express their decision preference by using the linguistic terms set [23]. The linguistic terms are denoted as $S = \{$}Very poor} (VP), }Poor} (P), }Slight Poor} (SP), }Medium} (M), }Slight Good} (SG), }Good} (G), }Very Good} (VG)}.

Step 2. Obtain the interval type-2 fuzzy evaluation matrix.

In this study, the trapezoid interval type-2 fuzzy numbers are utilized to express the linguistic decision preference information. The transformation from the linguistic information into trapezoid interval type-2 fuzzy numbers can be represented in Table 1.

3.2. Stage 2: Construct the Group Decision Matrix. In the course of robot evaluation and selection, the decision-makers may not be equal in the realistic process because of their knowledge, experience, and different work department. These different characteristics may lead to different preference and evaluation information under the same alternative and criteria [46]. Therefore, the different preference information should be aggregated into a group decision matrix by considering the different importance weights of decision-makers. Generally, the aggregation operators are regarded as one of the most effective techniques to fuse evaluation information from various decision-makers. In this context, we introduce the aggregation operator into IT2TrFNs to perform the process of construction of group evaluation matrix. As one of the most widely used aggregator operators, the WAA operator is selected to aggregate evaluation information from various decision-makers [47]. Therefore, we use the IT2TrFN-WAA operator to deal with the construction of group evaluation matrix problem.

Step 3. Determine the importance weight of each decision-maker.

First, according to the knowledge, experience, and work department of each decision-maker, we assign the importance weight $\{\omega^1, \ldots, \omega^k, \ldots, \omega^t\}$ to each decision-maker.

Step 4. Obtain the group decision matrix using WAA operator.

Let $\tilde{\tilde{x}}_{ij}^k$ be the evaluation information of alternative robot a_i with respect to criterion c_j from kth decision-maker. Assume that $Y = [\tilde{\tilde{y}}_{ij}]_{m\times n}$ is the group evaluation matrix, in which $\tilde{\tilde{y}}_{ij}$ is still an IT2TrFN. Then, $\tilde{\tilde{y}}_{ij}$ obtained by using the IT2TrFN-WAA operator can be expressed as follows:

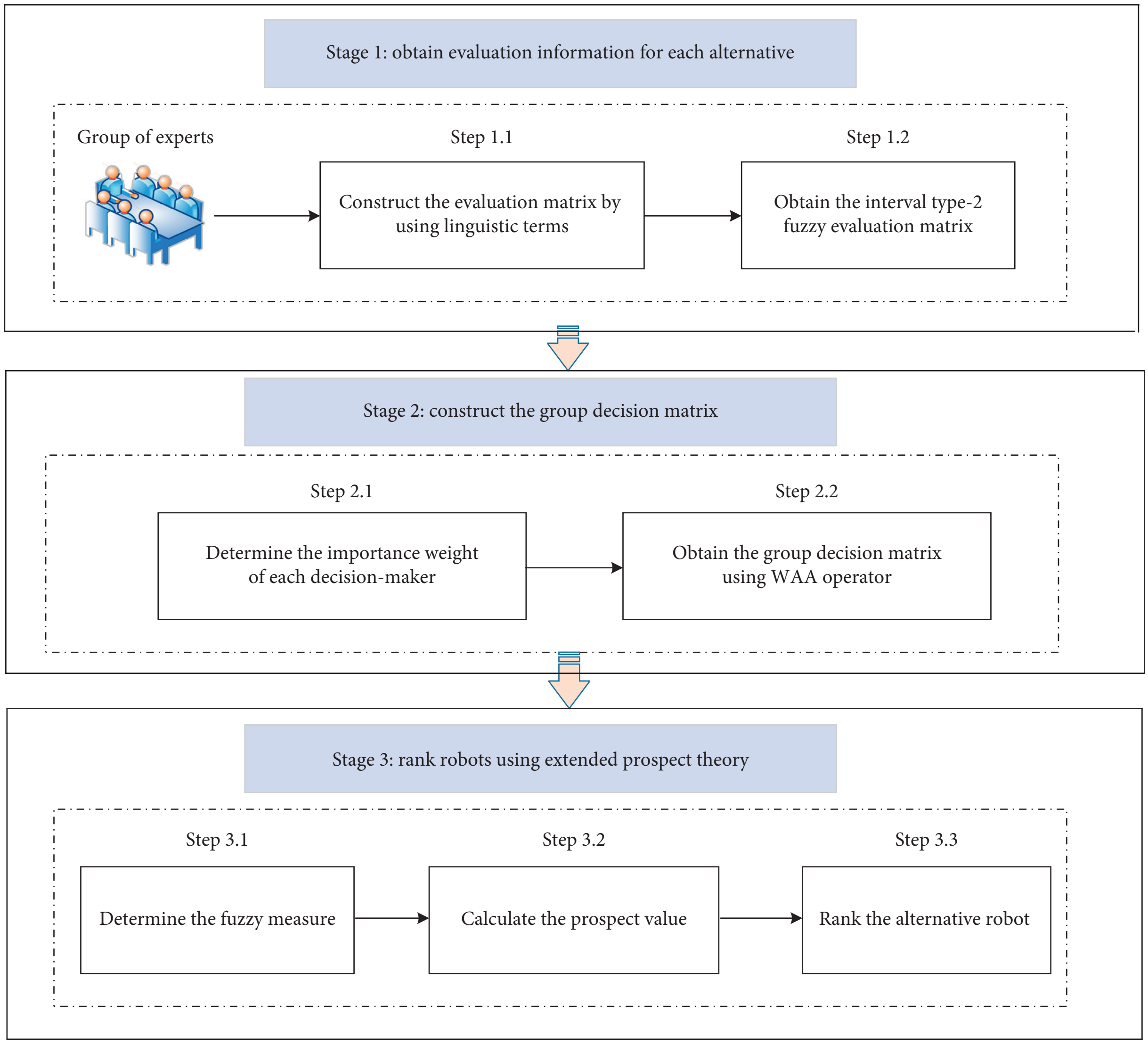

Figure 3: The flowchart of the proposed method.

Table 1: Linguistic terms and their corresponding IT2TrFNs [40].

Linguistic terms	Interval type-2 trapezoid fuzzy number
Very high (VH)	[(0.9, 1, 1, 1; 1); (0.95, 1, 1, 1; 0.9)]
High (H)	[(0.7, 0.9, 0.9, 1; 1); (0.8, 0.9, 0.9, 0.95; 0.9)]
Slightly high (SH)	[(0.5, 0.7, 0.7, 0.9; 1),(0.6, 0.7, 0.7, 0.8; 0.9)]
Medium (M)	[(0.3, 0.5, 0.5, 0.7; 1),(0.4, 0.5, 0.5, 0.6; 0.9)]
Slight low (SL)	[(0.1, 0.3, 0.3, 0.5; 1),(0.2, 0.3, 0.3, 0.4; 0.9)]
Low (L)	[(0, 0.1, 0.1, 0.3; 1),(0.05, 0.1, 0.1, 0.2; 0.9)]
Very low (VL)	[(0, 0, 0, 0.1; 1),(0, 0, 0, 0.05; 0.9)]

$$\begin{aligned}\tilde{\tilde{y}}_{ij} &= \text{IT2TrFN} - \text{WAA}_\omega\left(\tilde{\tilde{x}}_{ij}^1, \ldots, \tilde{\tilde{x}}_{ij}^k, \ldots, \tilde{\tilde{x}}_{ij}^t\right) = \sum_{k=1}^{t} \omega^k \tilde{\tilde{x}}_{ij}^k \\ &= \begin{bmatrix} \left(\sum_{k=1}^{t}\omega^k x_{ij1}^{kL}, \sum_{k=1}^{t}\omega^k x_{ij2}^{kL}, \sum_{k=1}^{t}\omega^k x_{ij3}^{kL}, \sum_{k=1}^{t}\omega^k x_{ij4}^{kL}; \min\left(h_{ij}^{1L}, h_{ij}^{2L}, \ldots, h_{ij}^{tL}\right)\right), \\ \left(\sum_{k=1}^{t}\omega^k x_{ij1}^{kU}, \sum_{k=1}^{t}\omega^k x_{ij2}^{kU}, \sum_{k=1}^{t}\omega^k x_{ij3}^{kU}, \sum_{k=1}^{t}\omega^k x_{ij4}^{kU}; \min\left(h_{ij}^{1U}, h_{ij}^{2U}, \ldots, h_{ij}^{tU}\right)\right) \end{bmatrix}.\end{aligned} \tag{16}$$

3.3. Stage 3: Rank Robots Using Extended Prospect Theory. In Stage 3, the priority of each alternative robot is calculated by constructing an extended prospect theory-based prioritization approach. In this prioritization approach, the risk preference of decision-makers and interaction relationships among criteria are taken into account. First, the distance measure of IT2TrFNs is introduced to determine the fuzzy measure. Then, the extended prospect theory based on Choquet integral is proposed to determine the ranking order of each alternative robot. The main steps of the extended prospect theory-based prioritization approach are described as follows:

Step 5. Determine the fuzzy measures of criteria.

In general, the fuzzy measure of each criterion is always assigned beforehand, which depends on the judgment of decision-makers. The fuzzy measure obtained in this way is a subjective result that may cause a misleading decision-making result. Consequently, an objective method for determining fuzzy measure is necessary for the priority calculating process. In such case, drawing the experience of [44, 45], a developed distance measure-based weighting method is utilized to determine the fuzzy measure of each criterion. In what follows, the developed distance measure-based method for determining fuzzy measure is presented as follows.

The first step of this method is to identify the positive and negative evaluation values, which can be completed as the following form:

$$y_j^+ = \begin{cases} \max_i \tilde{\tilde{y}}_{ij}, \text{if } j \in J_1, \\ \min_i \tilde{\tilde{y}}_{ij}, \text{if } j \in J_2, \end{cases} \tag{17}$$

$$y_j^- = \begin{cases} \min_i \tilde{\tilde{y}}_{ij}, \text{if } j \in J_1, \\ \max_i \tilde{\tilde{y}}_{ij}, \text{if } j \in J_2. \end{cases} \tag{18}$$

where J_1 and J_2 are the set of benefit and cost criteria, respectively.

Remark 1. The comparison between each two IT2TrFNs can be performed by using the method proposed by Qin et al. [40], which is also shown in Definition 5.

Next, we can obtain the distance between each evaluation rating and the positive and negative evaluation values as follows:

$$d^+\left(\tilde{\tilde{y}}_{ij}, y_j^+\right) = \left|R\left(\tilde{\tilde{y}}_{ij}, \tilde{\tilde{1}}\right) - R\left(\tilde{\tilde{y}}_j^+, \tilde{\tilde{1}}\right)\right|, \tag{19}$$

$$d^-\left(\tilde{\tilde{y}}_{ij}, y_j^-\right) = \left|R\left(\tilde{\tilde{y}}_{ij}, \tilde{\tilde{1}}\right) - R\left(\tilde{\tilde{y}}_j^-, \tilde{\tilde{1}}\right)\right|. \tag{20}$$

Then, the dispersion of each criterion can be expressed as follows:

$$\zeta_j = \frac{\sum_{i=1}^m d^+\left(\tilde{\tilde{y}}_{ij}, y_j^+\right)}{\sum_{i=1}^m d^+\left(\tilde{\tilde{y}}_{ij}, y_j^+\right) + \sum_{i=1}^m d^-\left(\tilde{\tilde{y}}_{ij}, y_j^-\right)}. \tag{21}$$

Finally, according to the experience in literature [45, 46], the fuzzy measure of each criterion can be determined as follows:

$$\phi\left(c_j\right) = \zeta_j. \tag{22}$$

Step 6. Calculate the prospect value.

According to the discussion mentioned above, current robot selection approaches are insufficient to determine optimal robot by considering the risk preference of decision-makers and interactive relationships among criteria. Although the prospect theory can depict the risk preference of decision-makers, it is unable to model the interactive relationships among criteria. Thus, we extend the prospect theory with Choquet integral into priority calculation problem by considering decision-makers' risk preference and interactive criteria. The extended prospect theory-based prioritization approach is described as follows.

First, in order to subjectively determine the reference point, we use equations (18) and (19) to identify the positive and negative reference points under each criterion. The reference point can be denoted as the following form:

$$\tilde{x}_j^0 = \begin{cases} \tilde{x}_j^{+0} = x_j^+, \\ \tilde{x}_j^{-0} = x_j^-. \end{cases} \tag{23}$$

Next, the value functions under positive and negative reference point can be defined as follows:

$$v^+(x_{ij}) = \begin{cases} \left[d\left(x_{ij}, x_j^{+0}\right)\right]^\alpha, & \text{if } x_{ij} \geq x_j^{+0}, \\ -\theta\left[d\left(x_{ij}, x_j^{+0}\right)\right]^\beta & \text{if } x_{ij} < x_j^{+0}, \end{cases} \tag{24}$$

$$v^-(x_{ij}) = \begin{cases} \left[d\left(x_{ij}, x_j^{-0}\right)\right]^\alpha, & \text{if } x_{ij} \geq x_j^{-0}, \\ -\theta\left[d\left(x_{ij}, x_j^{-0}\right)\right]^\beta, & \text{if } x_{ij} < x_j^{-0}. \end{cases} \tag{25}$$

Then, the prospect value of each alternative robot under positive and negative reference point can be obtained by the following form:

$$v^+(a_i) = \sum_{j=1}^{n} v^+\left(x_{i(j)}\right)\left[\phi\left(c_{(j)}\right) - \phi\left(c_{(j-1)}\right)\right], \tag{26}$$

$$v^-(a_i) = \sum_{j=1}^{n} v^-\left(x_{i(j)}\right)\left[\phi\left(c_{(j)}\right) - \phi\left(c_{(j-1)}\right)\right]. \tag{27}$$

Step 7. Rank the alternative robot.

Motivated by the mechanism of the TOPSIS method, the priority of each alternative robot can be derived as follows:

$$p_i = \frac{v^+(a_i)}{v^+(a_i) + v^-(a_i)}. \tag{28}$$

3.4. The Solving Procedures for Robots Selection Problem. According to the substeps of the above three stages, we can make a summary of the solving procedures for robot selection problem, which is shown as follows:

Step 1. Construct the linguistic evaluation matrix by inviting a group of experts $e_k = (k = 1, 2, \ldots, t)$.

Step 2. Obtain the interval type-2 fuzzy matrix $X^k = [\tilde{\tilde{x}}_{ij}^k]_{m\times n}$ $(k = 1, 2, \ldots, t)$ by using the transformation rules expressed in Table 2.

Step 3. Obtain the group decision matrix $Y = [\tilde{\tilde{y}}_{ij}]_{m\times n}$ by virtue of the IT2TrFN-WAA operator, which is denoted as equation (17).

Step 4. Determine the value functions $v^+ = (x_{ij})$ and $v^- = (x_{ij})$ under positive and negative reference points by using equations (18)–(21) and equations (24)–(26), respectively.

Step 5. By utilizing equations (27) and (28), we can calculate the prospect value of each alternative robot.

Step 6. Calculate the priority of each alternative robot using equation (28).

4. Case Study

In this section, an illustrative example of robot evaluation and selection problem in the auto industry [19] is presented to demonstrate the application of the proposed robot evaluation and selection method. In addition, the sensitivity analysis is conducted to illustrate the validity and characteristics of the proposed robot evaluation and selection method.

Table 2: Linguistic evaluation information from decision-maker e_1.

	c_1	c_2	c_3	c_4	c_5	c_6	c_7
a_1	P	VG	SP	G	SG	VG	G
a_2	G	SP	P	M	VG	VG	SG
a_3	VG	SP	P	M	M	SP	SG
a_4	SP	M	G	G	M	SG	M
a_5	VG	P	SP	P	SP	M	SP
a_6	P	SG	SG	SP	VG	G	VG
a_7	G	SP	VP	SP	SP	VP	SP
a_8	VG	P	P	VP	P	SP	M

4.1. Problem Description. After the preliminary simulation, there are eight alternative robots $A = (a_1, a_2, \ldots, a_8)$, which satisfies the production technique demand of the auto industry. Three experts $\{e_1, e_2, e_3\}$ from different departments and fields are invited to construct a group of experts for the evaluation and selection of the optimal robot for this auto industry, who are assigned the importance weight vector $\{0.3, 0.5, 0.2\}$ by considering the heterogeneous characteristics of decision-makers. Drawing the experience of reference [2], seven criteria $\{c_1, c_2, \ldots, c_7\}$ are selected to analyze the alternative robot evaluation and selection problem in the auto industry, which is provided in Figure 4.

4.2. Illustration of the Proposed Hybrid Method. In what follows, we adopt the proposed hybrid robot evaluation and selection method to evaluate and prioritize the performance of all of the eight alternative robots, which includes the following specific steps:

Step 1. Construct the evaluation matrix by using linguistic terms.

According to the linguistic term sets shown in Table 1, the linguistic evaluation information from three decision-makers is provided in Tables 2–4.

Step 2. Obtain the interval type-2 fuzzy matrix.

According to the linguistic evaluation information provided in Tables 2–4 and the transformation rules shown in Table 1, we can obtain the interval type-2 fuzzy matrix for the alternative robot evaluation and selection process, which are shown as Tables 5–7.

Step 3. Obtain the group decision matrix.

According to the importance weight of each expert, the final group decision matrix is constructed via equation (17), shown in Tables 8 and 9.

Step 4. Determine the value function.

First, we calculate the distances $d^+(\tilde{\tilde{y}}_{ij}, y_j^+)$ and $d^-(\tilde{\tilde{y}}_{ij}, y_j^-)$ by using equations (18)–(21), shown in Tables 10 and 11. Then, the value functions under positive and negative reference point are obtained by using equations (25) and (26) by taking $\alpha = \beta = 0.88$ and $\theta = 2.25$. The results are shown in Tables 12 and 13.

Step 5. Determine the prospect value.

Based on the value functions obtained by Step 4, the prospect value of each robot is derived by using equations (27) and (28), which is provided in Table 14.

In order to clearly illustrate the calculation process of prospect value, the alternative robot c_1 in term of criterion c_1 is selected as an example. First, the fuzzy measures of the evaluation criteria are determined by using equations (22) and (23). Then, the fuzzy densities of these criteria are calculated through equations (14) and (15). The result is shown in the following form. Next, according to equations (27) and (28), the prospect values of alternative robot under positive and negative reference points are determined as follows.

$$\begin{aligned}
\phi(c_1) &= 0.347,\\
\phi(c_2) &= 0.448,\\
\phi(c_3) &= 0.453,\\
\phi(c_4) &= 0.478,\\
\phi(c_5) &= 0.552,\\
\phi(c_6) &= 0.576,\\
\phi(c_7) &= 0.522,\\
\phi(c_1, c_2) &= 0.644,\\
\phi(c_1, c_3) &= 0.647,\\
\phi(c_1, c_4) &= 0.664,\\
\phi(c_1, c_5) &= 0.713,\\
\phi(c_1, c_6) &= 0.728,\\
\phi(c_1, c_7) &= 0.693,\\
\phi(c_1, c_2, c_3) &= 0.811,\\
\phi(c_1, c_2, c_4) = 0.821, \ldots, \phi(c_1, c_2, c_7) &= 0.837,\\
\phi(c_1, c_3, c_4) = 0.822, \phi(c_1, c_3, c_5) = 0.849, \ldots, \phi(c_1, c_3, c_7) &= 0.838,\\
\phi(c_1, c_4, c_5) = 0.857, \phi(c_1, c_4, c_6) = 0.887, \phi(c_1, c_4, c_7) &= 0.847,\\
\phi(c_1, c_5, c_6) = 0.887, \phi(c_1, c_5, c_7) = 0.870, \phi(c_1, c_6, c_7) &= 0.878,\\
\phi(c_1, c_2, c_3, c_4) = 0.909, \ldots, \phi(c_1, c_2, c_3, c_7) = 0.918, \phi(c_1, c_2, c_4, c_5) = 0.929, \phi(c_1, c_2, c_4, c_6) &= 0.934,\\
\phi(c_1, c_2, c_4, c_7) = 0.923, \phi(c_1, c_3, c_4, c_5) = 0.930, \ldots, \phi(c_1, c_3, c_4, c_7) = 0.924, \phi(c_1, c_4, c_5, c_6) &= 0.949,\\
\phi(c_1, c_4, c_5, c_7) = 0.941, \phi(c_1, c_4, c_6, c_7) = 0.945, \ldots, \phi(c_1, c_5, c_6, c_7) = 0.955, \phi(c_1, c_2, c_3, c_4, c_5) &= 0.969,\\
\phi(c_1, c_2, c_3, c_4, c_6) = 0.972, \ldots, \phi(c_1, c_2, c_3, c_6, c_7) = 0.969, \phi(c_1, c_2, c_4, c_5, c_6) &= 0.980,\\
\phi(c_1, c_2, c_4, c_5, c_7) = 0.976, \phi(c_1, c_2, c_4, c_6, c_7) = 0.978, \phi(c_1, c_2, c_5, c_6, c_7) &= 0.984,\\
\phi(c_1, c_3, c_4, c_5, c_6) = 0.981, \ldots, \phi(c_1, c_3, c_4, c_6, c_7) = 0.978, \phi(c_1, c_3, c_5, c_6, c_7) &= 0.984,\\
\phi(c_1, c_4, c_5, c_6, c_7) = 0.986, \phi(c_1, c_2, c_3, c_4, c_5, c_6) = 0.991, \phi(c_1, c_2, c_3, c_4, c_5, c_7) &= 0.989,\\
\phi(c_1, c_2, c_4, c_5, c_6, c_7) = 0.994, \ldots, \phi(c_1, c_3, c_4, c_5, c_6, c_7) = 0.994, \phi(c_1, c_2, c_3, c_4, c_5, c_6, c_7) &= 1,\\
v^{+}(a_1) = 0.347 * 0.862 + 0.008 * + \cdots + 0.191 * (-0.107) &= 0.131,\\
v^{-}(a_2) = 0.005 * (-0.245) + 0.055 * 0.973 + \cdots + 0.133 * (0.809) &= 0.764.
\end{aligned} \tag{29}$$

Step 6. Calculate the final priority of each robot.

According to the prospect values of each alternative robot under positive and negative reference points, the final priorities of alternative robots are determined by using equation (29), which is shown in Table 15. In order to visualize the priorities of the eight alternative robots, a radar plot is provided to show the ranking order of each alternative robot, which is depicted in Figure 5.

According to the result provided in Table 15 and Figure 5, it is obvious that the priority ranking order of each

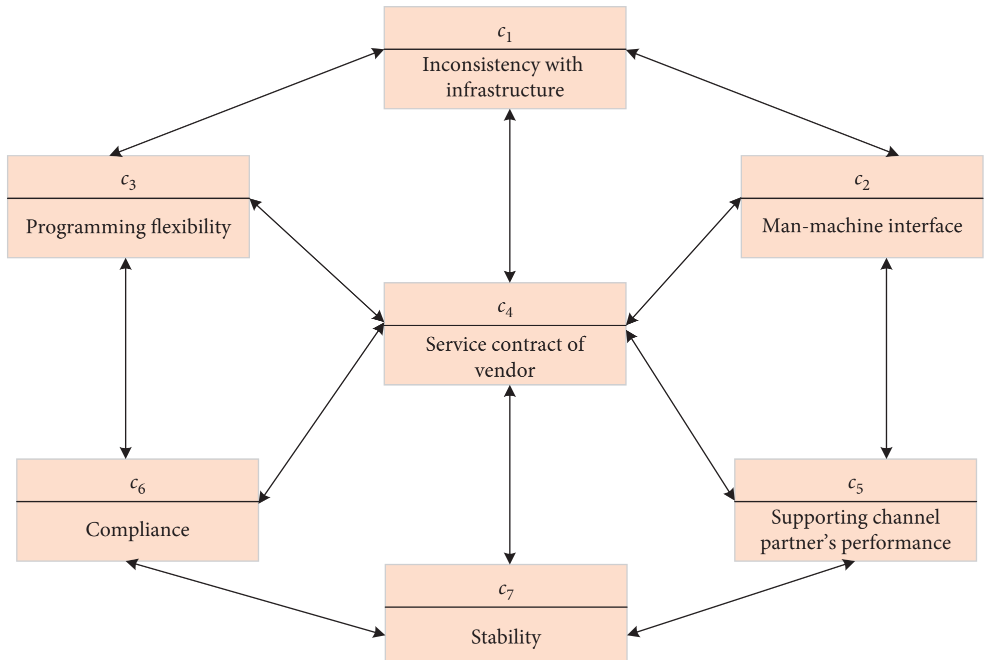

Figure 4: The criteria for alternative robot selection.

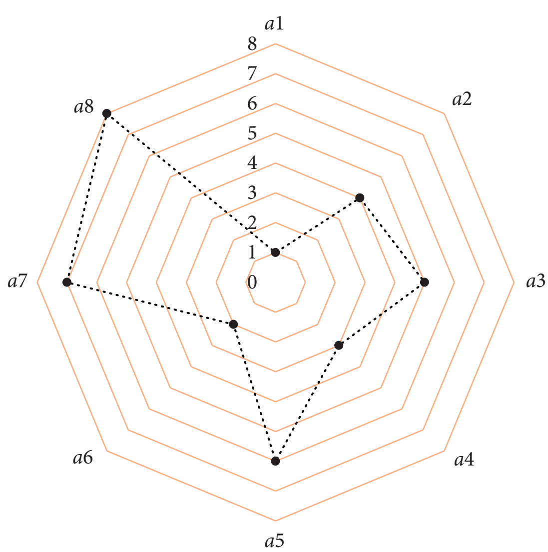

Figure 5: The radar plot showing the ranking result of robots.

alternative robot is $a_1 \succ a_6 \succ a_4 \succ \cdots \succ a_7 \succ a_8$. Accordingly, the most optimal alternative robot is a_1.

4.3. Sensitivity Analysis and Discussion. As mentioned in Section 3.2, the risk preference of each decision-maker may be different. The parameter θ is utilized to depict the risk loss aversion coefficient of decision-makers. In order to analyze the influence of risk preference of decision-makers, we adopt different values of parameter θ and evaluate the priority of each alternative robot. The corresponding result is provided in Table 16. In addition, Figure 6 displays the priority of each alternative robot obtained with different values of parameter θ.

As shown in Table 16 and Figure 6, it is obvious to find that the priorities $p_i\,(i = 1, 2, \ldots, 8)$ of the eight alternative robots calculated by different values of parameter θ are quite different. From Figure 6, it is apparent that the priority of each alternative robot reduces with an increase of the risk loss aversion coefficient θ. The sensitivity analysis shows that the priorities p_i are influenced by the changing of the risk loss aversion coefficient. It also highlights that the priority of each alternative robot is indeed affected by risk preference of decision-makers.

In addition, Table 16 displays the priority ranking order of each alternative robot obtained by the different values of parameter θ (from 1 to 3) which are the same in this illustrative case study. The result indicates that the ranking order of each alternative robot is not sensitive to the values of parameter θ. In other words, although the robot evaluation and selection process involves various values of the risk loss aversion coefficient θ, the priority ranking order of each alternative robot still remains consistent. This also verifies the robustness of the proposed robot evaluation and selection approach.

4.4. Comparison Analysis and Discussion. In order to further illustrate the rationality and applicability of the proposed robot evaluation and selection approach, a comparison study is conducted with a number of previous alternative robot evaluation and selection methods, which includes hesitant fuzzy linguistic MULTIMOORA (Method 1) [2], interval type-2 fuzzy VIKOR (Method 2) [19], interval type-2 fuzzy TOPSIS (Method 3) [53], and interval-valued fuzzy TOPSIS (Method 4) [17]. In order to visualize the ranking order of the eight alternative robots determined by using different approaches, we provided a diagram based on

Table 3: Linguistic evaluation information from decision-maker e_2.

	c_1	c_2	c_3	c_4	c_5	c_6	c_7
a_1	P	VG	G	SG	G	G	G
a_2	VG	SP	VP	SP	G	M	SP
a_3	G	VP	M	SP	M	P	G
a_4	P	SP	SG	M	SP	SG	M
a_5	G	SP	SP	VP	P	SP	M
a_6	VP	VG	G	SP	VG	G	VG
a_7	VG	M	P	M	SP	P	P
a_8	G	VP	P	P	VP	M	M

Table 4: Linguistic evaluation information from decision-maker e_3.

	c_1	c_2	c_3	c_4	c_5	c_6	c_7
a_1	P	VG	M	G	G	VG	VG
a_2	G	SP	SP	M	SG	VG	M
a_3	SG	VP	P	M	M	SP	SG
a_4	SP	M	G	VG	SP	SG	M
a_5	VG	VP	SP	P	M	SP	SP
a_6	P	SG	SG	P	G	SG	VG
a_7	VG	G	SP	M	SP	VP	SP
a_8	VG	VP	SP	VP	P	SP	VP

Table 5: Interval type-2 fuzzy evaluation matrix from decision-maker e_1.

	c_1	c_2	c_3	c_4	c_5	c_6	c_7
a_1	[(0, 0.1, 0.1, 0.3; 1), (0.05, 0.1, 0.1, 0.2; 0.9)]	[(0.9, 1, 1, 1; 1), (0.95, 1, 1, 1; 0.9)]	[(0.1, 0.3, 0.3, 0.5; 1), (0.2, 0.3, 0.3, 0.4; 0.9)]	[(0.7, 0.9, 0.9, 1; 1), (0.8, 0.9, 0.9, 0.95; 0.9)]	[(0.5, 0.7, 0.7, 0.9; 1), (0.6, 0.7, 0.7, 0.8; 0.9)]	[(0.9, 1, 1, 1; 1), (0.95, 1, 1, 1; 0.9)]	[(0.7, 0.9, 0.9, 1; 1), (0.8, 0.9, 0.9, 0.95; 0.9)]
a_2	[(0.7, 0.9, 0.9, 1; 1), (0.8, 0.9, 0.9, 0.95; 0.9)]	[(0.1, 0.3, 0.3, 0.5; 1), (0.2, 0.3, 0.3, 0.4; 0.9)]	[(0, 0.1, 0.1, 0.3; 1), (0.05, 0.1, 0.1, 0.2; 0.9)]	[(0.3, 0.5, 0.5, 0.7; 1), (0.4, 0.5, 0.5, 0.6; 0.9)]	[(0.9, 1, 1, 1; 1), (0.95, 1, 1, 1; 0.9)]	[(0.9, 1, 1, 1; 1), (0.95, 1, 1, 1; 0.9)]	[(0.5, 0.7, 0.7, 0.9; 1), (0.6, 0.7, 0.7, 0.8; 0.9)]
a_3	[(0.9, 1, 1, 1; 1), (0.95, 1, 1, 1; 0.9)]	[(0.1, 0.3, 0.3, 0.5; 1), (0.2, 0.3, 0.3, 0.4; 0.9)]	[(0, 0.1, 0.1, 0.3; 1), (0.05, 0.1, 0.1, 0.2; 0.9)]	[(0.3, 0.5, 0.5, 0.7; 1), (0.4, 0.5, 0.5, 0.6; 0.9)]	[(0.3, 0.5, 0.5, 0.7; 1), (0.4, 0.5, 0.5, 0.6; 0.9)]	[(0.1, 0.3, 0.3, 0.5; 1), (0.2, 0.3, 0.3, 0.4; 0.9)]	[(0.5, 0.7, 0.7, 0.9; 1), (0.6, 0.7, 0.7, 0.8; 0.9)]
a_4	[(0.1, 0.3, 0.3, 0.5; 1), (0.2, 0.3, 0.3, 0.4; 0.9)]	[(0.3, 0.5, 0.5, 0.7; 1), (0.4, 0.5, 0.5, 0.6; 0.9)]	[(0.7, 0.9, 0.9, 1; 1), (0.8, 0.9, 0.9, 0.95; 0.9)]	[(0.7, 0.9, 0.9, 1; 1), (0.8, 0.9, 0.9, 0.95; 0.9)]	[(0.3, 0.5, 0.5, 0.7; 1), (0.4, 0.5, 0.5, 0.6; 0.9)]	[(0.5, 0.7, 0.7, 0.9; 1), (0.6, 0.7, 0.7, 0.8; 0.9)]	[(0.3, 0.5, 0.5, 0.7; 1), (0.4, 0.5, 0.5, 0.6; 0.9)]
a_5	[(0.9, 1, 1, 1; 1), (0.95, 1, 1, 1; 0.9)]	[(0, 0.1, 0.1, 0.3; 1), (0.05, 0.1, 0.1, 0.2; 0.9)]	[(0.1, 0.3, 0.3, 0.5; 1), (0.2, 0.3, 0.3, 0.4; 0.9)]	[(0, 0.1, 0.1, 0.3; 1), (0.05, 0.1, 0.1, 0.2; 0.9)]	[(0.1, 0.3, 0.3, 0.5; 1), (0.2, 0.3, 0.3, 0.4; 0.9)]	[(0.3, 0.5, 0.5, 0.7; 1), (0.4, 0.5, 0.5, 0.6; 0.9)]	[(0.1, 0.3, 0.3, 0.5; 1), (0.2, 0.3, 0.3, 0.4; 0.9)]
a_6	[(0, 0.1, 0.1, 0.3; 1), (0.05, 0.1, 0.1, 0.2; 0.9)]	[(0.5, 0.7, 0.7, 0.9; 1), (0.6, 0.7, 0.7, 0.8; 0.9)]	[(0.5, 0.7, 0.7, 0.9; 1), (0.6, 0.7, 0.7, 0.8; 0.9)]	[(0.1, 0.3, 0.3, 0.5; 1), (0.2, 0.3, 0.3, 0.4; 0.9)]	[(0.9, 1, 1, 1; 1), (0.95, 1, 1, 1; 0.9)]	[(0.7, 0.9, 0.9, 1; 1), (0.8, 0.9, 0.9, 0.95; 0.9)]	[(0.9, 1, 1, 1; 1), (0.95, 1, 1, 1; 0.9)]
a_7	[(0.7, 0.9, 0.9, 1; 1), (0.8, 0.9, 0.9, 0.95; 0.9)]	[(0.1, 0.3, 0.3, 0.5; 1), (0.2, 0.3, 0.3, 0.4; 0.9)]	[(0, 0, 0, 0.1; 1), (0, 0, 0, 0.05; 0.9)]	[(0.1, 0.3, 0.3, 0.5; 1), (0.2, 0.3, 0.3, 0.4; 0.9)]	[(0.1, 0.3, 0.3, 0.5; 1), (0.2, 0.3, 0.3, 0.4; 0.9)]	[(0, 0, 0, 0.1; 1), (0, 0, 0, 0.05; 0.9)]	[(0.1, 0.3, 0.3, 0.5; 1), (0.2, 0.3, 0.3, 0.4; 0.9)]
a_8	[(0.9, 1, 1, 1; 1), (0.95, 1, 1, 1; 0.9)]	[(0, 0.1, 0.1, 0.3; 1), (0.05, 0.1, 0.1, 0.2; 0.9)]	[(0, 0.1, 0.1, 0.3; 1), (0.05, 0.1, 0.1, 0.2; 0.9)]	[(0, 0, 0, 0.1; 1), (0, 0, 0, 0.05; 0.9)]	[(0, 0.1, 0.1, 0.3; 1), (0.05, 0.1, 0.1, 0.2; 0.9)]	[(0.1, 0.3, 0.3, 0.5; 1), (0.2, 0.3, 0.3, 0.4; 0.9)]	[(0.3, 0.5, 0.5, 0.7; 1), (0.4, 0.5, 0.5, 0.6; 0.9)]

Table 17 to display the result of comparative analysis, which can be expressed as Figure 7.

Kendall's coefficient of concordance in Table 17 is 0.966, which almost approaches to 1. In addition, the alternative robots a_1, a_6, and a_4 have the most highest priority in all of the five approaches. This means that that there is extremely high homogeneity between the proposed robot evaluation and selection approach and the other four approaches. It also indicates that the proposed hybrid approach is valid to evaluate and select the optimal robot for industry. On the other hand, there are still some inconsistencies between the proposed hybrid method and the other four methods. These different ranking results can be explained as following comparative analyses.

Table 6: Interval type-2 fuzzy evaluation matrix from decision-maker e_2.

	c_1	c_2	c_3	c_4	c_5	c_6	c_7
a_1	[(0, 0.1, 0.1, 0.3; 1), (0.05, 0.1, 0.1, 0.2; 0.9)]	[(0.9, 1, 1, 1; 1), (0.95, 1, 1, 1; 0.9)]	[(0.7, 0.9, 0.9, 1; 1), (0.8, 0.9, 0.9, 0.95; 0.9)]	[(0.5, 0.7, 0.7, 0.9; 1), (0.6, 0.7, 0.7, 0.8; 0.9)]	[(0.7, 0.9, 0.9, 1; 1), (0.8, 0.9, 0.9, 0.95; 0.9)]	[(0.7, 0.9, 0.9, 1; 1), (0.8, 0.9, 0.9, 0.95; 0.9)]	[(0.7, 0.9, 0.9, 1; 1), (0.8, 0.9, 0.9, 0.95; 0.9)]
a_2	[(0.9, 1, 1, 1; 1), (0.95, 1, 1, 1; 0.9)]	[(0.1, 0.3, 0.3, 0.5; 1), (0.2, 0.3, 0.3, 0.4; 0.9)]	[(0, 0, 0, 0.1; 1), (0, 0, 0, 0.05; 0.9)]	[(0.1, 0.3, 0.3, 0.5; 1), (0.2, 0.3, 0.3, 0.4; 0.9)]	[(0.7, 0.9, 0.9, 1; 1), (0.8, 0.9, 0.9, 0.95; 0.9)]	[(0.3, 0.5, 0.5, 0.7; 1), (0.4, 0.5, 0.5, 0.6; 0.9)]	[(0.1, 0.3, 0.3, 0.5; 1), (0.2, 0.3, 0.3, 0.4; 0.9)]
a_3	[(0.7, 0.9, 0.9, 1; 1), (0.8, 0.9, 0.9, 0.95; 0.9)]	[(0, 0, 0, 0.1; 1), (0, 0, 0, 0.05; 0.9)]	[(0.3, 0.5, 0.5, 0.7; 1), (0.4, 0.5, 0.5, 0.6; 0.9)]	[(0.1, 0.3, 0.3, 0.5; 1), (0.2, 0.3, 0.3, 0.4; 0.9)]	[(0.3, 0.5, 0.5, 0.7; 1), (0.4, 0.5, 0.5, 0.6; 0.9)]	[(0, 0.1, 0.1, 0.3; 1), (0.05, 0.1, 0.1, 0.2; 0.9)]	[(0.7, 0.9, 0.9, 1; 1), (0.8, 0.9, 0.9, 0.95; 0.9)]
a_4	[(0, 0.1, 0.1, 0.3; 1), (0.05, 0.1, 0.1, 0.2; 0.9)]	[(0.1, 0.3, 0.3, 0.5; 1), (0.2, 0.3, 0.3, 0.4; 0.9)]	[(0.5, 0.7, 0.7, 0.9; 1), (0.6, 0.7, 0.7, 0.8; 0.9)]	[(0.3, 0.5, 0.5, 0.7; 1), (0.4, 0.5, 0.5, 0.6; 0.9)]	[(0.1, 0.3, 0.3, 0.5; 1), (0.2, 0.3, 0.3, 0.4; 0.9)]	[(0.5, 0.7, 0.7, 0.9; 1), (0.6, 0.7, 0.7, 0.8; 0.9)]	[(0.3, 0.5, 0.5, 0.7; 1), (0.4, 0.5, 0.5, 0.6; 0.9)]
a_5	[(0.7, 0.9, 0.9, 1; 1), (0.8, 0.9, 0.9, 0.95; 0.9)]	[(0.1, 0.3, 0.3, 0.5; 1), (0.2, 0.3, 0.3, 0.4; 0.9)]	[(0.1, 0.3, 0.3, 0.5; 1), (0.2, 0.3, 0.3, 0.4; 0.9)]	[(0, 0, 0, 0.1; 1), (0, 0, 0, 0.05; 0.9)]	[(0, 0.1, 0.1, 0.3; 1), (0.05, 0.1, 0.1, 0.2; 0.9)]	[(0.1, 0.3, 0.3, 0.5; 1), (0.2, 0.3, 0.3, 0.4; 0.9)]	[(0, 0, 0, 0.1; 1), (0, 0, 0, 0.05; 0.9)]
a_6	[(0, 0, 0, 0.1; 1), (0, 0, 0, 0.05; 0.9)]	[(0.9, 1, 1, 1; 1), (0.95, 1, 1, 1; 0.9)]	[(0.7, 0.9, 0.9, 1; 1), (0.8, 0.9, 0.9, 0.95; 0.9)]	[(0.1, 0.3, 0.3, 0.5; 1), (0.2, 0.3, 0.3, 0.4; 0.9)]	[(0.9, 1, 1, 1; 1), (0.95, 1, 1, 1; 0.9)]	[(0.7, 0.9, 0.9, 1; 1), (0.8, 0.9, 0.9, 0.95; 0.9)]	[(0.9, 1, 1, 1; 1), (0.95, 1, 1, 1; 0.9)]
a_7	[(0.9, 1, 1, 1; 1), (0.95, 1, 1, 1; 0.9)]	[(0.3, 0.5, 0.5, 0.7; 1), (0.4, 0.5, 0.5, 0.6; 0.9)]	[(0, 0.1, 0.1, 0.3; 1), (0.05, 0.1, 0.1, 0.2; 0.9)]	[(0.3, 0.5, 0.5, 0.7; 1), (0.4, 0.5, 0.5, 0.6; 0.9)]	[(0.1, 0.3, 0.3, 0.5; 1), (0.2, 0.3, 0.3, 0.4; 0.9)]	[(0, 0.1, 0.1, 0.3; 1), (0.05, 0.1, 0.1, 0.2; 0.9)]	[(0, 0.1, 0.1, 0.3; 1), (0.05, 0.1, 0.1, 0.2; 0.9)]
a_8	[(0.7, 0.9, 0.9, 1; 1), (0.8, 0.9, 0.9, 0.95; 0.9)]	[(0, 0, 0, 0.1; 1), (0, 0, 0, 0.05; 0.9)]	[(0, 0.1, 0.1, 0.3; 1), (0.05, 0.1, 0.1, 0.2; 0.9)]	[(0, 0.1, 0.1, 0.3; 1), (0.05, 0.1, 0.1, 0.2; 0.9)]	[(0, 0, 0, 0.1; 1), (0, 0, 0, 0.05; 0.9)]	[(0.3, 0.5, 0.5, 0.7; 1), (0.4, 0.5, 0.5, 0.6; 0.9)]	[(0.3, 0.5, 0.5, 0.7; 1), (0.4, 0.5, 0.5, 0.6; 0.9)]

Table 7: Interval type-2 fuzzy evaluation matrix from decision-maker e_3.

	c_1	c_2	c_3	c_4	c_5	c_6	c_7
a_1	[(0, 0.1, 0.1, 0.3; 1), (0.05, 0.1, 0.1, 0.2; 0.9)]	[(0.9, 1, 1, 1; 1), (0.95, 1, 1, 1; 0.9)]	[(0.3, 0.5, 0.5, 0.7; 1), (0.4, 0.5, 0.5, 0.6; 0.9)]	[(0.7, 0.9, 0.9, 1; 1), (0.8, 0.9, 0.9, 0.95; 0.9)]	[(0.7, 0.9, 0.9, 1; 1), (0.8, 0.9, 0.9, 0.95; 0.9)]	[(0.9, 1, 1, 1; 1), (0.95, 1, 1, 1; 0.9)]	[(0.9, 1, 1, 1; 1), (0.95, 1, 1, 1; 0.9)]
a_2	[(0.7, 0.9, 0.9, 1; 1), (0.8, 0.9, 0.9, 0.95; 0.9)]	[(0.1, 0.3, 0.3, 0.5; 1), (0.2, 0.3, 0.3, 0.4; 0.9)]	[(0.1, 0.3, 0.3, 0.5; 1), (0.2, 0.3, 0.3, 0.4; 0.9)]	[(0.3, 0.5, 0.5, 0.7; 1), (0.4, 0.5, 0.5, 0.6; 0.9)]	[(0.5, 0.7, 0.7, 0.9; 1), (0.6, 0.7, 0.7, 0.8; 0.9)]	[(0.9, 1, 1, 1; 1), (0.95, 1, 1, 1; 0.9)]	[(0.3, 0.5, 0.5, 0.7; 1), (0.4, 0.5, 0.5, 0.6; 0.9)]
a_3	[(0.5, 0.7, 0.7, 0.9; 1), (0.6, 0.7, 0.7, 0.8; 0.9)]	[(0, 0, 0, 0.1; 1), (0, 0, 0, 0.05; 0.9)]	[(0, 0.1, 0.1, 0.3; 1), (0.05, 0.1, 0.1, 0.2; 0.9)]	[(0.3, 0.5, 0.5, 0.7; 1), (0.4, 0.5, 0.5, 0.6; 0.9)]	[(0.3, 0.5, 0.5, 0.7; 1), (0.4, 0.5, 0.5, 0.6; 0.9)]	[(0.1, 0.3, 0.3, 0.5; 1), (0.2, 0.3, 0.3, 0.4; 0.9)]	[(0.5, 0.7, 0.7, 0.9; 1), (0.6, 0.7, 0.7, 0.8; 0.9)]
a_4	[(0.1, 0.3, 0.3, 0.5; 1), (0.2, 0.3, 0.3, 0.4; 0.9)]	[(0.3, 0.5, 0.5, 0.7; 1), (0.4, 0.5, 0.5, 0.6; 0.9)]	[(0.7, 0.9, 0.9, 1; 1), (0.8, 0.9, 0.9, 0.95; 0.9)]	[(0.9, 1, 1, 1; 1), (0.95, 1, 1, 1; 0.9)]	[(0.1, 0.3, 0.3, 0.5; 1), (0.2, 0.3, 0.3, 0.4; 0.9)]	[(0.5, 0.7, 0.7, 0.9; 1), (0.6, 0.7, 0.7, 0.8; 0.9)]	[(0.3, 0.5, 0.5, 0.7; 1), (0.4, 0.5, 0.5, 0.6; 0.9)]
a_5	[(0.9, 1, 1, 1; 1), (0.95, 1, 1, 1; 0.9)]	[(0, 0, 0, 0.1; 1), (0, 0, 0, 0.05; 0.9)]	[(0.1, 0.3, 0.3, 0.5; 1), (0.2, 0.3, 0.3, 0.4; 0.9)]	[(0, 0.1, 0.1, 0.3; 1), (0.05, 0.1, 0.1, 0.2; 0.9)]	[(0.3, 0.5, 0.5, 0.7; 1), (0.4, 0.5, 0.5, 0.6; 0.9)]	[(0.1, 0.3, 0.3, 0.5; 1), (0.2, 0.3, 0.3, 0.4; 0.9)]	[(0.1, 0.3, 0.3, 0.5; 1), (0.2, 0.3, 0.3, 0.4; 0.9)]
a_6	[(0, 0.1, 0.1, 0.3; 1), (0.05, 0.1, 0.1, 0.2; 0.9)]	[(0.5, 0.7, 0.7, 0.9; 1), (0.6, 0.7, 0.7, 0.8; 0.9)]	[(0.5, 0.7, 0.7, 0.9; 1), (0.6, 0.7, 0.7, 0.8; 0.9)]	[(0, 0.1, 0.1, 0.3; 1), (0.05, 0.1, 0.1, 0.2; 0.9)]	[(0.7, 0.9, 0.9, 1; 1), (0.8, 0.9, 0.9, 0.95; 0.9)]	[(0.5, 0.7, 0.7, 0.9; 1), (0.6, 0.7, 0.7, 0.8; 0.9)]	[(0.9, 1, 1, 1; 1), (0.95, 1, 1, 1; 0.9)]
a_7	[(0.9, 1, 1, 1; 1), (0.95, 1, 1, 1; 0.9)]	[(0.7, 0.9, 0.9, 1; 1), (0.8, 0.9, 0.9, 0.95; 0.9)]	[(0.1, 0.3, 0.3, 0.5; 1), (0.2, 0.3, 0.3, 0.4; 0.9)]	[(0.3, 0.5, 0.5, 0.7; 1), (0.4, 0.5, 0.5, 0.6; 0.9)]	[(0.1, 0.3, 0.3, 0.5; 1), (0.2, 0.3, 0.3, 0.4; 0.9)]	[(0, 0, 0, 0.1; 1), (0, 0, 0, 0.05; 0.9)]	[(0.1, 0.3, 0.3, 0.5; 1), (0.2, 0.3, 0.3, 0.4; 0.9)]
a_8	[(0.9, 1, 1, 1; 1), (0.95, 1, 1, 1; 0.9)]	[(0, 0, 0, 0.1; 1), (0, 0, 0, 0.05; 0.9)]	[(0.1, 0.3, 0.3, 0.5; 1), (0.2, 0.3, 0.3, 0.4; 0.9)]	[(0, 0, 0, 0.1; 1), (0, 0, 0, 0.05; 0.9)]	[(0, 0.1, 0.1, 0.3; 1), (0.05, 0.1, 0.1, 0.2; 0.9)]	[(0.1, 0.3, 0.3, 0.5; 1), (0.2, 0.3, 0.3, 0.4; 0.9)]	[(0, 0, 0, 0.1; 1), (0, 0, 0, 0.05; 0.9)]

Table 8: The group evaluation matrix.

	a_1	a_2	a_3	a_4
c_1	[(0, 0.1, 0.1, 0.3; 1), (0.05, 0.1, 0.1, 0.2; 0.9)]	[(0.8, 0.95, 0.95, 1; 1), (0.88, 0.95, 0.95, 0.98; 0.9)]	[(0.72, 0.89, 0.89, 0.98; 1), (0.81, 0.89, 0.89, 0.94; 0.9)]	[(0.05, 0.2, 0.2, 0.4; 1), (0.13, 0.2, 0.2, 0.3; 0.9)]
c_2	[(0.9, 1, 1, 1; 1), (0.95, 1, 1, 1; 0.9)]	[(0.1, 0.3, 0.3, 0.5; 1), (0.2, 0.3, 0.3, 0.4; 0.9)]	[(0.03, 0.09, 0.09, 0.22; 1), (0.06, 0.09, 0.09, 0.16; 0.9)]	[(0.2, 0.4, 0.4, 0.6; 1), (0.3, 0.4, 0.4, 0.5; 0.9)]
c_3	[(0.44, 0.64, 0.64, 0.79; 1), (0.54, 0.64, 0.64, 0.72; 0.9)]	[(0.02, 0.09, 0.09, 0.24; 1), (0.06, 0.09, 0.09, 0.17; 0.9)]	[(0.15, 0.3, 0.3, 0.5; 1), (0.23, 0.3, 0.3, 0.4; 0.9)]	[(0.6, 0.8, 0.8, 0.95; 1), (0.7, 0.8, 0.8, 0.88; 0.9)]
c_4	[(0.6, 0.8, 0.8, 0.95; 1), (0.7, 0.8, 0.8, 0.88; 0.9)]	[(0.2, 0.4, 0.4, 0.6; 1), (0.3, 0.4, 0.4, 0.5; 0.9)]	[(0.2, 0.4, 0.4, 0.6; 1), (0.3, 0.4, 0.4, 0.5; 0.9)]	[(0.54, 0.72, 0.72, 0.85; 1), (0.63, 0.72, 0.72, 0.79; 0.9)]
c_5	[(0.64, 0.84, 0.84, 0.97; 1), (0.74, 0.84, 0.84, 0.91; 0.9)]	[(0.72, 0.89, 0.89, 0.98; 1), (0.81, 0.89, 0.89, 0.94; 0.9)]	[(0.3, 0.5, 0.5, 0.7; 1), (0.4, 0.5, 0.5, 0.6; 0.9)]	[(0.16, 0.36, 0.36, 0.56; 1), (0.26, 0.36, 0.36, 0.46; 0.9)]
c_6	[(0.8, 0.95, 0.95, 1; 1), (0.88, 0.95, 0.95, 0.98; 0.9)]	[(0.6, 0.75, 0.75, 0.85; 1), (0.68, 0.75, 0.75, 0.8; 0.9)]	[(0.05, 0.2, 0.2, 0.4; 1), (0.13, 0.2, 0.2, 0.3; 0.9)]	[(0.5, 0.7, 0.7, 0.9; 1), (0.6, 0.7, 0.7, 0.8; 0.9)]
c_7	[(0.74, 0.92, 0.92, 1; 1), (0.83, 0.92, 0.92, 0.96; 0.9)]	[0.26, 0.46, 0.46, 0.66; 1], (0.36, 0.46, 0.46, 0.56; 0.9)]	[(0.6, 0.8, 0.8, 0.95; 1), (0.7, 0.8, 0.8, 0.88; 0.9)]	[(0.3, 0.5, 0.5, 0.7; 1), (0.4, 0.5, 0.5, 0.6; 0.9)]

Table 9: The group evaluation matrix.

	a_5	a_6	a_7	a_8
c_1	[(0.8, 0.95, 0.95, 1; 1), (0.88, 0.95, 0.95, 0.98; 0.9)]	[(0, 0.05, 0.05, 0.2; 1), (0.03, 0.05, 0.05, 0.13; 0.9)]	[(0.84, 0.97, 0.97, 1; 1), (0.91, 0.97, 0.97, 0.99; 0.9)]	[(0.8, 0.95, 0.95, 1; 1), (0.88, 0.95, 0.95, 0.98; 0.9)]
c_2	[(0.05, 0.18, 0.18, 0.36; 1), (0.12, 0.18, 0.18, 0.27; 0.9)]	[(0.7, 0.85, 0.85, 0.95; 1), (0.978, 0.85, 0.85, 0.9; 0.9)]	[(0.32, 0.52, 0.52, 0.7; 1), (0.42, 0.52, 0.52, 0.61; 0.9)]	[(0, 0.03, 0.03, 0.16; 1), (0.02, 0.03, 0.03, 0.1; 0.9)]
c_3	[(0.1, 0.3, 0.3, 0.5; 1), (0.2, 0.3, 0.3, 0.4; 0.9)]	[(0.6, 0.8, 0.8, 0.95; 1), (0.7, 0.8, 0.8, 0.88; 0.9)]	[(0.02, 0.11, 0.11, 0.28; 1), (0.07, 0.11, 0.11, 0.2; 0.9)]	[(0.02, 0.14, 0.14, 0.34; 1), (0.08, 0.14, 0.14, 0.24; 0.9)]
c_4	[(0, 0.05, 0.05, 0.2; 1), (0.03, 0.05, 0.05, 0.13; 0.9)]	[(0.08, 0.26, 0.26, 0.46; 1), (0.17, 0.26, 0.26, 0.36; 0.9)]	[(0.24, 0.44, 0.44, 0.64; 1), (0.3, 0.44, 0.44, 0.54; 0.9)]	[(0, 0.05, 0.05, 0.2; 1), (0.03, 0.05, 0.05, 0.13; 0.9)]
c_5	[(0.09, 0.24, 0.24, 0.44; 1), (0.17, 0.24, 0.24, 0.34; 0.9)]	[(0.86, 0.98, 0.98, 1; 1), (0.92, 0.98, 0.98, 0.99; 0.9)]	[(0.1, 0.3, 0.3, 0.5; 1), (0.2, 0.3, 0.3, 0.4; 0.9)]	[(0, 0.05, 0.05, 0.2; 1), (0.03, 0.05, 0.05, 0.13; 0.9)]
c_6	[(0.16, 0.36, 0.36, 0.56; 1), (0.26, 0.36, 0.36, 0.46; 0.9)]	[(0.66, 0.86, 0.86, 0.98; 1), (0.76, 0.86, 0.86, 0.92; 0.9)]	[(0, 0.05, 0.05, 0.2; 0.9), (0.03, 0.05, 0.05, 0.13; 0.9)]	[(0.2, 0.4, 0.4, 0.6; 1), (0.3, 0.4, 0.4, 0.58; 0.9)]
c_7	[(0.05, 0.15, 0.15, 0.3; 0.9), (0.1, 0.15, 0.15, 0.23; 0.9)]	[((0.9, 1, 1, 1; 1), (0.95, 1, 1, 1; 0.9)]	[(0.05, 0.2, 0.2, 0.4; 1), (0.13, 0.2, 0.2, 0.3; 0.9)]	[(0.24, 0.4, 0.4, 0.58; 1), (0.32, 0.4, 0.4, 0.49; 0.9)]

Table 10: The result of distance c_1.

	c_1	c_2	c_3	c_4	c_5	c_6	c_7
a_1	0.845	0.969	0.601	0.809	0.844	0.917	0.786
a_2	0.008	0.352	0.000	0.419	0.874	0.728	0.360
a_3	0.051	0.072	0.252	0.419	0.519	0.200	0.689
a_4	0.725	0.452	0.761	0.716	0.379	0.719	0.400
a_5	0.008	0.200	0.272	0.000	0.240	0.379	0.000
a_6	0.925	0.860	0.761	0.272	0.929	0.862	0.817
a_7	0.000	0.567	0.032	0.459	0.319	0.000	0.080
a_8	0.008	0.000	0.080	0.000	0.000	0.419	0.280

Table 11: The result of distance c_1.

	c_1	c_2	c_3	c_4	c_5	c_6	c_7
a_1	0.080	0.000	0.160	0.000	0.085	0.000	0.031
a_2	0.917	0.617	0.761	0.389	0.055	0.189	0.457
a_3	0.874	0.897	0.509	0.389	0.410	0.717	0.128
a_4	0.200	0.517	0.000	0.092	0.550	0.198	0.417
a_5	0.917	0.769	0.489	0.809	0.689	0.538	0.817
a_6	0.000	0.109	0.000	0.537	0.000	0.055	0.000
a_7	0.925	0.402	0.729	0.349	0.610	0.917	0.737
a_8	0.917	0.969	0.680	0.809	0.929	0.498	0.537

Table 12: The value function under positive reference point.

	c_1	c_2	c_3	c_4	c_5	c_6	c_7
a_1	0.862	0.000	−0.449	0.000	−0.257	0.000	−0.107
a_2	0.014	−1.472	−1.769	−0.980	−0.176	−0.520	−1.130
a_3	0.073	−2.045	−1.241	−0.980	−1.026	−1.680	−0.369
a_4	0.754	−1.260	0.000	−0.276	−1.329	−0.541	−1.043
a_5	0.014	−1.786	−1.199	−1.866	−1.621	−1.304	−1.884
a_6	0.934	−0.319	0.000	−1.301	0.000	−0.176	0.000
a_7	0.000	−1.008	−1.703	−0.891	−1.455	−2.085	−1.720
a_8	0.014	−2.188	−1.603	−1.866	−2.109	−1.281	−1.303

Table 13: The value function under negative reference point.

	c_1	c_2	c_3	c_4	c_5	c_6	c_7
a_1	−0.245	0.973	0639	0.829	0.861	0.927	0.809
a_2	−2.085	0.399	0.000	0.465	0.888	0.756	0.407
a_3	−1.998	0.098	0.297	0.465	0.562	0.243	0.720
a_4	−0.546	0.467	0.786	0.746	0.426	0.748	0.446
a_5	−2.085	0.243	0.318	0.000	0.285	0.426	0.000
a_6	0.000	0.876	0.786	0.318	0.937	0.877	0.837
a_7	−2.101	0.607	0.049	0.504	0.366	0.000	0.109
a_8	−2.085	0.000	0.109	0.000	0.000	0.465	0.326

Table 14: The prospect value of each robot.

	a_1	a_2	a_3	a_4	a_5	a_6	a_7	a_8
V^+ (a_1)	0.131	−0.938	−1.099	−0.496	−1.182	−0.107	−1.244	−1.307
V^- (a_2)	0.764	0.241	0.213	0.472	0.058	0.585	0.064	0.019

Table 15: The final priority of each robot.

	a_1	a_2	a_3	a_4	a_5	a_6	a_7	a_8
Priority	0.895	−0.696	−0.885	−0.025	−1.124	0.478	−1.181	−1.288
Rank	1	4	5	3	6	2	7	8

Table 16: The result of sensitivity analysis.

	$\theta = 1$		$\theta = 1.5$		$\theta = 2$		$\theta = 2.25$		$\theta = 2.5$		$\theta = 3$	
	p_i	Rank	p_i	Rank	p_i	Rank	p_i	Rank	p_i	Rank	p_i	Rank
a_1	0.989	1	0.951	1	0.914	1	0.895	1	0.876	1	0.838	1
a_2	−0.167	4	−0.379	4	−0.591	4	−0.696	4	−0.892	4	−1.014	4
a_3	−0.255	5	−0.507	5	−0.759	5	−0.885	5	−1.011	5	−1.263	5
a_4	0.398	3	0.229	3	0.060	3	−0.025	3	−0.109	3	−0.278	3
a_5	−0.459	6	−0.725	6	−0.991	6	−1.124	6	−1.258	6	−1.524	6
a_6	0.718	2	0.622	2	0.526	2	0.478	2	0.430	2	0.334	2
a_7	−0.483	7	−0.762	7	−1.041	7	−1.181	7	−1.320	7	−1.599	7
a_8	−0.553	8	−0.847	8	−1.141	8	−1.288	8	−1.435	8	−1.729	8

The priority ranking orders of alternative robots a_5 and a_7 are different under the proposed approach and Method 1. In Method 1, the alternative robot a_7 has a higher priority than alternative robot a_5. However, the priority of each alternative robot obtained by the proposed approach shows that the alternative robot a_5 has a higher priority than alternative robot a_7. These inconsistencies can be explained as follows. First, although the original evaluation ratings of a_7 are higher than a_5, the prospect value of a_5 is higher than a_7 when the two reference points are adopted in the proposed approach. Second, the interactive relationships among criteria are not considered in Method 1, which have an influence on the determination of weights of criteria and priority of each alternative robot. Therefore, the priority ranking order of each alternative robot derived by the proposed approach is more reasonable.

Table 17: The result of comparison analysis.

	Method 1	Method 2	Method 3	Method 4	The proposed method
a_1	1	1	1	1	1
a_2	4	5	5	5	4
a_3	5	4	4	4	5
a_4	3	3	3	3	3
a_5	7	7	8	8	6
a_6	2	2	2	2	2
a_7	6	6	6	6	7
a_8	8	8	7	7	8

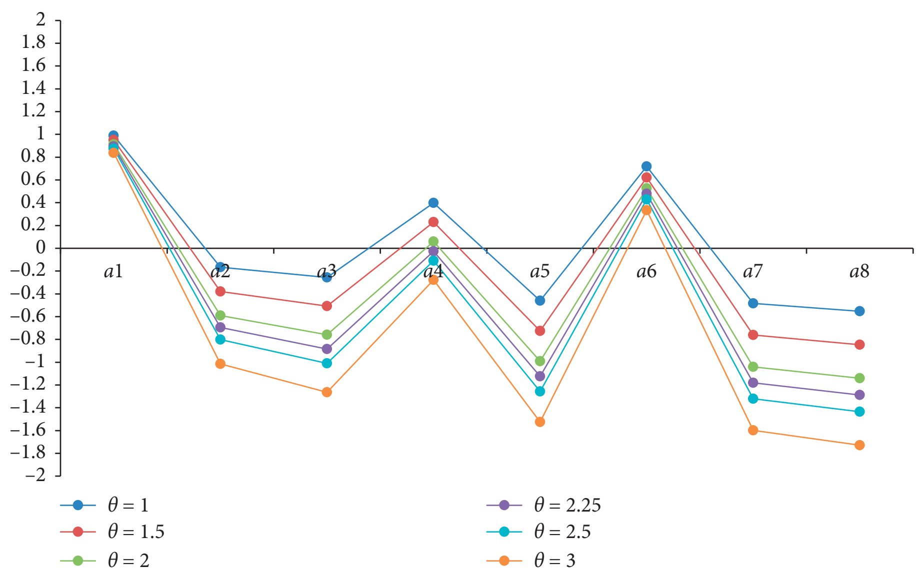

Figure 6: The priorities of robots with different values of parameter $p_i\,(i = 1, 2, \ldots, 8)$.

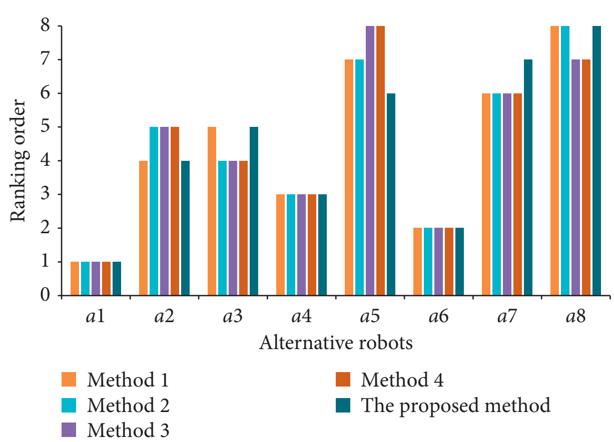

Figure 7: The result of comparative analysis.

The priority ranking orders of alternative robots a_2, a_3, a_5, and a_7 calculated by the Method 2 are inconsistent with these obtained by using the proposed approach. Although the interval type-2 fuzzy sets are adopted in both of the two methods, the different priority calculation mechanisms are utilized in the two methods. For example, the priority of each alternative robot determined by Method 2 shows that the alternative robot a_3 has a higher priority than a_2. Nevertheless, the result obtained by the proposed approach shows that alternative robot a_2 has a higher priority than a_3, which is more reasonable. This is because the original evaluation ratings and value functions of a_2 with respect to criteria c_2, c_5, and c_5 are significantly higher. This is also confirmed by the approach proposed by Liu et al. [2]. Accordingly, the proposed approach may be more reflective of the practical robot evaluation and selection problems.

The priority ranking orders of the eight alternative robots obtained by Method 3 and Method 4 are consistent. However, the worst alternative robot obtained by the two methods is a_5 and not a_8. This result is inconsistent with the other three approaches. Compared with the proposed approach, the priority ranking order of each alternative robot obtained by the two methods is unreliable. This unreliable result can be explained by the following reasons. First, similar to Method 2, Methods 3 and 4 are unable to model the risk preference of decision-maker and interactive relationships among criteria in the alternative robot evaluation and selection process. Second, in Methods 3 and 4, the way adopted to select ideal solution may lead to information loss in the alternative robot evaluation and selection process [2]. Thus, the priority ranking orders of alternative robots determined by the two methods may be unreliable.

According to the discussion mentioned above, the proposed robot evaluation and selection approach can obtain a more reasonable and reliable priority ranking result than the existing approaches. The advantages of the proposed approach can be summarized as follows:

(1) In the extended prospect theory, the positive and negative reference points are used as a substitute for single reference point. The using two reference points provides a more flexible and effective way to represent the complex risk preference of decision-maker in the robot evaluation and selection process.
(2) The distance measure of IT2TrFNs is incorporated into the developed Choquet integral for determining the fuzzy measure of each criterion. This cannot only provide a more objective means for modeling the interactive relationships among criteria but also provide a more reliable and reasonable result of robot evaluation and selection.
(3) The proposed hybrid framework is constructed based on the prospect theory and Choquet integral, which considers the decision-maker's risk preference and interactive criteria in the robot evaluation and selection process.

5. Conclusions

In this paper, a developed hybrid MCDA framework is proposed for addressing the robot evaluation and selection problem by considering the decision-maker's risk preference and interactive criteria under high uncertain environment. In the hybrid framework, the interval type-2 fuzzy set is adopted to express the uncertain evaluation information from various decision-makers. In addition, the distance measure of IT2TrFNs is incorporated into the Choquet integral to depict the interactive relationships among criteria. Furthermore, motived by the TOPSIS method, the extended prospect theory with two reference points is proposed to determine the optimal alternative robot by considering the risk preference of decision-maker and interactive relationships among criteria. Finally, the proposed approach is applied to evaluate and select an optimal robot in the auto industry. The illustrative example demonstrates the proposed hybrid framework in detail. Moreover, the sensitivity and comparison studies are conducted in the illustrative example. The results show the robustness, effectiveness, and advantages of the proposed framework.

We also point out some limitations of the developed robot evaluation and selection framework and directions of the future research. First, in the course of evaluation information aggregation, the importance weight of each decision-maker is determined by adopting a subjective weighting method, which may be highly dependent on the expert's personal judgments. For future research, the objective weight determination method is suggested to be used for obtaining the objective importance weight of each decision-maker. Second, only seven criteria are utilized to evaluate and select the optimal alternative robot. In the future, more related criteria should be considered to make more thorough and reasonable evaluation criteria. Third, the influence of decision-maker's capability on robot evaluation and selection is not considered in this research. Thus, the consensus-based decision-making approaches can be extended to this problem for overcoming this gap.

Data Availability

The research data are all provided in the manuscript.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Authors' Contributions

Guobao Zhang wrote the original manuscript. Shuping Cheng contributed reviewed and edited the manuscript. Guobao Zhang contributed to project administration and is responsible for funding acquisition.

Acknowledgments

This work was supported by the Youth Project of Anhui Province Philosophy and Social Sciences Planning (no. AHSKQ2016D25).

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