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A Novel Picture Fuzzy Set-Based Decision Approach for Consumer Trust Project Risk Assessment

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Abstract: Consumer trust projects have formed as a novel business idea to achieve industrial transformation and upgrade Chinese trust companies (consumer trust projects), and it is of great significance to identify risks and evaluate their ranking order based on risk priorities. Considering the complexity and uncertainty brought by the multiple stages and multiple subjects, an innovative decision system framework was proposed, integrating criteria interaction through inter-criteria correlation (CRITIC) and the decision-making method additive ratio assessment (ARAS) based on prospect theory (PT) under a picture fuzzy environment. The proposed decision system framework not only determines the weights of criteria by considering the correlation and conflict among them but also determines the risk priority and ranking order by considering the bounded rationality of decision makers (DMs). Subsequently, to demonstrate the efficiency and practicability of the proposed framework, this paper constructs a consumer trust project risk evaluation model that includes a risk evaluation index system consisting of twenty-two risk factors and four relevant criteria in a case study. Then, the established model is used in a specific consumer trust project to demonstrate the application of the proposed framework. After that, a sensitivity discussion and a comparative analysis are provided to demonstrate the introduced methodology's feasibility and necessity. The risk priority and ranking order calculated by the framework will give a reference for risk management of consumer trust projects.

Keywords: consumer trust; risk evaluation index system; multi-criteria decision making; picture fuzzy set; CRITIC; PT-ARAS

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1. Introduction

Since the outbreak of the financial crisis in 2008, trust companies have rapidly formed in China to fill the social fund gap and increase financing channels by carrying out shadow banking business [1,2]. So far, the development of the Chinese trust industry has evolved in two stages. In the first stage, the main responsibility of the trust industry was to act as the government's external financing and raise construction funds for local development outside the banking planning system, similar to the characteristics of banking in actual operation. In the second stage, with the promulgation of the Trust Law of the People's Republic of China, the orientation of the Chinese trust industry was made preliminarily clear—they are non-banking financial institutions that are chartered, hold financial licenses, and mainly engage in the trust business. As such, trust companies have returned to operating as trust businesses in a comprehensive way, mainly focusing on financing trust.

Trust companies are the main object of the Chinese trust industry, providing typical Chinese shadow banking. Outside the scope of public-sector supervision, trust companies operate based on strict financial control and developed credit chains. Without supervision, trust companies inevitably have various increased risks as the financial system develops, such as product design risks [3], credit risks, and default risks [4]. Further, under the pressure of China's economic slowdown and industrial structure transformation and upgrade, the redemption dilemma of trust products frequently appears.

Under these circumstances, risk management of trust projects has received attention from the China Banking and Insurance Regulatory Commission (CBIRC) from 2014 to 2016. In 2018, the release of Guiding Opinions on Regulating the Asset Management Business of Financial Institutions marked a new era of unified financial supervision. With the improvement and development of regulatory policies, uncertainty in the operation of trust businesses has been exacerbated, which leads to more unprecedented challenges. Therefore, trust companies urgently need to explore innovative businesses to achieve transformation and upgrade.

In recent years, with the continuous upgrading of the domestic consumption structure, residents' consumption demand presents a trend of diversification and individuation. In 2009, consumer finance, as a modern financial instrument that provided consumer loans to consumers of all levels was issued by the CBIRC. Since 2013, driven by government policies, the increasing development of e-commerce, and internet technologies, numerous studies have shown that the Chinese consumer finance market is developing rapidly and maturing [5–7]. At present, consumer finance constitutes a complete industrial chain, including the capital supply side, consumer finance service providers, and the capital demand side. Additionally, the consumer financial market has attracted the interest of financial institutions with great potential including commercial banks, licensed consumer finance companies, internet-based platforms, and trust companies.

Consumer trust projects are an innovative business idea derived by trust companies to act as consumer finance servicers, providing loans for consumers. Consumer trust projects not only create lucrative opportunities for trust companies but also bring greater risks and challenges. On the one hand, the relatively competitive market with continuous competition and development of policies and regulations published in the trust industry result in over credit, multiple debt problems, and credit risks [8]. On the other hand, the outbreak of COVID-19 in 2020 caused a dramatic slump in the global economy. The negative impact of the economic crisis was almost instantly observed in consumer finance [9]. The pandemic further increased the instability of consumer trust projects, which led to more overdue payments [10].

Specifically, consumer finance projects launched by trust companies are exposed to various risks including credit risk, which has been commonly discussed in consumer loans by scholars. However, there are fewer studies considering other risks or which take risk criteria into account to evaluate the priority and ranking order of identified risk factors in consumer trust projects. Risk identification and evaluation are crucial steps in comprehensive risk management in order to improve risk resilience [11]. Relevant literature indicates that risk mitigation measures taken according to different priorities of risk factors can reduce or even eliminate key risks and improve the efficiency of risk management so as to ensure the smooth implementation of projects [12]. Thus, there is great practical significance in carrying out a risk evaluation to achieve risk mitigation and control in consumer trust projects for trust companies.

The determination of risk priority and ranking order for a project is generally considered a multi-criteria decision-making (MCDM) problem [13,14]. MCDM technology, as a significant branch of operations research, due its high capability of determining risk ranking order based on several criteria, has been commonly implemented in various projects [15,16]. In the existing literature, MCDM to evaluate risks in the financial field is mainly used for financial risks in enterprises [17,18] and credit risks in financial institutions [19,20]. To the best of our knowledge, fewer studies have addressed risk evaluation of consumer trust projects as an MCDM problem and used a quantitative MCDM approach to determine risk priority and the ranking order of such projects.

During the evaluating process, uncertain and ambiguous risk evaluation information could be produced from DMs' judgment due to the variations of politics, economy, law, and the complexity of the ex ante forecast of the behavior itself. Under these circumstances, utilizing fuzzy numbers to describe uncertain decision-making information has been recognized as superior to, and more appropriate than, crisp numbers. Therefore, instead of describing risk information by crisp numbers, the existing fuzzy linguistic approaches have been widely applied to MCDM problems [21–23]. Fuzzy sets (FSs), introduced by Zadeh [24], were characterized as a membership function. Based on FSs, Intuitionistic fuzzy sets (IFSs), proposed by Atanassov [25], added a non-membership degree function. So far, FSs and IFSs can describe DMs' opinions by membership and non-membership grades which have been widely applied for risk assessment problems [26–29]. Yet, FSs and IFSs both ignore the opposition and refusal opinions of DMs', picture fuzzy sets (PFSs), proposed by Cường [30] as a supplement, including the membership degree of positive, neutral, negative, and refusal, can satisfy various types of DMs' answers [13]. By considering more parameters, picture fuzzy numbers (PFNs) can depict more complex situations and make assessing information more imprecise [31].

In many fuzzy MCDM problems, DMs' psychological characteristics are usually ignored directly; DMs are usually assumed to be rational in making decisions. In fact, due to the complexity of practical decision-making problems and the limitation of DMs' knowledge, the assumption of rational DMs tends to diverge from reality, which indicates the necessity of considering the bounded rationality of DMs. Prospect theory, founded by Kahneman and Tversky [32], considers behavior characteristics by integrating DMs' psychological perceptions into decision-making behavior analysis to reflect the actual decision-making process. It emphasizes that DMs select the alternatives according to their prospect value which represents the outcome of gain or loss compared with a reference point.

Therefore, the main purpose of this study is to develop a decision-making system framework by using MCDM technology to determine risk priority and ranking order in consumer trust projects which provide quantitative evidence for risk management in trust companies. In the proposed framework, criteria interaction through inter-criteria correlation (CRITIC) and the additive ratio assessment (ARAS) method combining prospect theory are extended into picture fuzzy environment. Among them, the CRITIC method, as the objective weight determining tool directly calculated from the evaluation matrix, determines the weights of criteria by considering the contrast intensity and conflict of each criterion simultaneously. Then, based on these calculated weight values, the ARAS method, combining prospect theory to consider DM's bounded rationality, can make the obtained risk priority and ranking order more reasonable.

Finally, the proposed framework is applied to obtain the risk priority and ranking order of risk factors which have been listed in the established evaluation index system based on a specific consumer trust project. The results of this case study are of considerable guiding significance for the company's manager in the adoption of reasonable risk mitigation measures in accordance with their priorities to reduce or even eliminate key risks.

The rest of this study is organized as follows. Section 2 presents a comprehensive review related to the study. Section 3 briefly introduces the research methodology, including some basic concepts of PFS and regret theory. In Section 4, an integrated decision system framework by integrating the CRITIC method and ARAS based on PT with picture fuzzy information is presented. In Section 5, the aforementioned decision system framework is applied to the risk evaluation of a specific consumer trust project based on the established risk evaluation model. Meanwhile, the effectiveness and superiority of the proposed decision system framework is validated. Section 6 summarizes some conclusions and provides some perspectives for further research.

2. Literature Review

The literature review is presented to provide better insights into the related research underlying this paper.

2.1. Picture Fuzzy Sets

The consumer trust project, as an innovative business, belongs to a format of consumer finance project launched by trust companies to seize the consumer financial market in

China. There is still limited literature concerned with this theme. Conversely, consumer finance is a hot issue that has been investigated concerned by scholars [33,34].

From the perspective of risk management, the related literature mainly focused on identifying, evaluating, and predicting risks from consumers, such as credit [35,36], payment [37], and default [38,39]. Zeng et al. [40] emphasized that the diversification of assessing factors is a significant feature of consumer credit risk assessment in the new stage. Rona-Tas and Guseva [41] indicated the identified evaluating factors mainly related to a wide variety of socioeconomic, demographic, and other criteria, or only those related to credit histories. So far, assessing factors such as age [42], gender [43], race [44], appearance [45,46], financial literacy [47], loan description [48,49], educational level [7], borrowers' internet behaviors [50], and macroeconomic factors [51] have been explored.

Meanwhile, there are also abundant achievements in the quantitative analysis of credit risk. Among these achievements, initial predicting models by using traditional statistical methods are investigated, such as linear discriminant analysis [35], logistic regression [39,52,53], and probit regression [54,55]. In addition, compared with the above methods, numerous studies show that the prediction precision of machine learning approaches, including SVMs [38,56], neural networks [57,58], decision trees [59,60], and genetic algorithms [57,61], is higher [62]. In addition, Dahooie et al. [19] and Du and Shi [20] focused on credit risk evaluation by using the MCDM method [63].

2.2. Applications of the CRITIC and ARAS Method

Generally, two key aspects in the process of MCDM technology are introduced, including forming a decision matrix, using it to determine criteria weights, and aggregating the information to evaluate decision alternatives [64].

In the framework of MCDM, determining the weights of criteria is a crucial choice for final results. According to weighting evaluation procedures, Peng [65] divided all weighting determination methods into objective and subjective weights. In other words, the distinction between the two categories depends on whether the weight is computed from the result or ascertained by DMs. CRITIC method as an objective method presented by Diakoulaki et al. [66] determined criteria weights relying on the amount of information the criteria itself contained. It indicates that criteria can be regarded as information sources, while weights that represent the importance of all criteria can reflect the amount of information contained in each of them. Considering the criteria with characteristics of information sources, Zeleny [67] considered the contrast intensity of each criterion quantified by the standard deviation (SD) or entropy that formed the original objective method. Therefore, measuring the contrast intensity of each criterion is the basis of the CRITIC method. On this basis, Diakoulaki et al. [66] added the second dimension of the conflict between different criteria which can be quantified by the correlation coefficient (CRC). Therefore, the SD and CRC calculated simultaneously from the evaluation matrix aim to extract as much information contained in the evaluation criteria as possible for improving the veracity of weighting determination. To some extent, compared with other objective methods under picture fuzzy information, CRITIC not only reflects the intrinsic information of data transmission but also approximates the value of subjective weight [68]. Thus, the CRITIC method has been demonstrated to assess effectively objective weights in significant MCDM problems [69]. So far, CRITIC has been applied under a fuzzy environment to solve the selection of third-party logistics providers [70–72], construction equipment [73], and so on [74,75].

Meanwhile, there are also numerous effective tools used in solving MCDM problems to achieve the task of ranking decision alternatives under different fuzzy environments [76]. The traditional ARAS method proposed by Zavadskas et al. [77] as an innovative MCDM technique which obtains ranking orders by assessing the performance ratio of each alternative to the ideal alternative is suitable for dealing with complex phenomena effortlessly [78]. In other words, the ARAS method determines the ranking order of decision alternatives by comparing the assessed performance ratio. According to Zamani et al. [79], the ARAS method has several advantages: (i) the computations are comprehensible; (ii) the concepts are rather logical and simple; (iii) the priority weights are obtained by comparisons. Therefore, this classical technique can yield accurate, realistic results in evaluating various alternatives based on easy processes and receives plenty of applications [80–83].

As discussed above, existing risk management for consumer finance has mainly focused on analyzing just three risks—credit risk, payment risk, and default risk—from consumers instead of all the dimensions. To the best of our knowledge, there is little literature discussing an MCDM technology to obtain risk priority and the ranking order for the project. Meanwhile, no studies integrates DMs' psychological perceptions into the decision-making process by using the ARAS method combining the prospect theory to determine risk ranking order under the fuzzy environment. Hence, to fill these gaps, this paper suggests the proposed framework, which includes the weight determination by the CRITIC method and the ARAS method combining prospect theory (PT-ARAS) under the picture fuzzy environment. The proposed framework aims to deal with uncertain and imprecise evaluating information described by picture fuzzy numbers, determine criteria weights by CRTIC, and obtain priority and ranking order for risks in consumer trust projects based on the PT-ARAS method, while the proposed framework is applied for a specific consumer trust project.

3. Preliminaries

In this section, some basic concepts of picture fuzzy sets and prospect theory are reviewed for readers to understand this paper better. Then, based on these preliminaries, the proposed framework under picture fuzzy environment is divided into three phases.

3.1. Picture Fuzzy Sets

Cường [30] proposed that the picture fuzzy sets (PFSs) satisfy various types of DMs' answers, including positive, neutral, negative, and refusal. Based on considering more parameters, picture fuzzy numbers (PFNs) can depict more complex situations and make assessing information more imprecise, especially in risk evaluation for DMs [31]. To date, PFSs have been increasingly extended in the risk evaluation of energy performance contracting projects [12], construction projects [14], agroforestry biomass power generation projects [84], and other MCDM problems [85,86]. In this paper, PFNs will be used to describe uncertain and ambiguous risk evaluation information expressed by DMs in consumer trust projects. Further, some basic concepts of PFSs are reviewed as follows.

Definition 1 ([30]). *Let X be a non-empty set. A picture fuzzy set A on the universe X is defined as follows:*

$$A = \{ \langle x, \mu_A(x), \eta_A(x), \nu_A(x) \rangle | x \in X \} \tag{1}$$

where $\mu_A(x), \eta_A(x), \nu_A(x): X \to [0,1]$, and $0 \leq \mu_A(x) + \eta_A(x) + \nu_A(x) \leq 1, \forall x \in X$. The functions $\mu_A(x)$, $\eta_A(x)$, and $\nu_A(x)$, respectively, represent the degrees of positive, neutral, and negative membership of element x in A. Moreover, the degree of refusal membership of x in A is defined as $\pi_A(x) = 1 - (\mu_A(x) + \eta_A(x) + \nu_A(x))$. For convenience, we call the symbol $A = \langle \mu_A, \eta_A, \nu_A \rangle$ a PFN.

Definition 2 ([87]). *Let $A = \langle \mu_A, \eta_A, \nu_A \rangle$ be a PFN. Then the score function of a PFN can be expressed as*:

$$S(A) = \frac{(1 + \mu_A - \nu_A)}{2}, \; S(A) \in [0,1]. \tag{2}$$

Definition 3 ([88,89]). *Let $A = \langle \mu_A, \eta_A, \nu_A \rangle$ and $B = \langle \mu_B, \eta_B, \nu_B \rangle$ be two PFNs, and $\lambda > 0$. Then the arithmetic operations of PFNs are expressed as follows*:

(1) $A \oplus B = \langle 1 - (1 - \mu_A)(1 - \mu_B), \eta_A\eta_B, (\eta_A + \nu_A)(\eta_B + \nu_B) - \eta_A\eta_B \rangle$;
(2) $A \otimes B = \langle (\mu_A + \eta_A)(\mu_B + \eta_B) - \eta_A\eta_B, \eta_A\eta_B, 1 - (1 - \nu_A)(1 - \nu_B) \rangle$;

(3) $\lambda A = \left\langle 1-(1-\mu_A)^{\lambda}, (\eta_A)^{\lambda}, (\eta_A+\nu_A)^{\lambda}-(\eta_A)^{\lambda} \right\rangle$;

(4) $A^{\lambda} = \left\langle (\mu_A+\eta_A)^{\lambda}-(\eta_A)^{\lambda}, (\eta_A)^{\lambda}, 1-(1-v_A)^{\lambda} \right\rangle$.

Definition 4 ([90]). *Let $\delta_j = (\mu_j, \eta_j, \nu_j)$ $(j = 1, 2, \cdots, n)$ be a set of PFNs. Then the picture fuzzy weighted averaging (PFWA) operator is given by*:

$$PFWA_W(\delta_1, \delta_2, \cdots \delta_n) = \left\langle 1-\prod_{j=1}^{n}\left(1-\mu_{\delta_j}\right)^{\omega_j}, \prod_{j=1}^{n}\left(\eta_{\delta_j}\right)^{\omega_j}, \prod_{j=1}^{n}\left(\nu_{\delta_j}+\eta_{\delta_j}\right)^{\omega_j}-\prod_{j=1}^{n}\left(\eta_{\delta_j}\right)^{\omega_j} \right\rangle \quad (3)$$

where $\omega = (\omega_1, \cdots, \omega_n)^T$ is the weight of $\delta_j (j = 1, 2, \cdots, n)$, $\omega_j \in [0, 1]$and $\sum_{j=1}^{n} \omega_j = 1$.

Definition 5 ([12]). *Assuming $A = \{a_1, a_2, \cdots, a_n\}$ and $B = \{b_1, b_2, \cdots, b_n\}$ are two PFSs. The normalized picture fuzzy Euclidean distance between A* and *B is computed as below*:

$$d(A, B) = \sqrt{\frac{1}{2n}\sum_{i=1}^{n}\left(\left|\mu_{A_i}-\mu_{B_i}\right|^2+\left|\eta_{A_i}-\eta_{B_i}\right|^2+\left|\nu_{A_i}-\nu_{B_i}\right|^2+\left|\pi_{A_i}-\pi_{B_i}\right|^2\right)}. \quad (4)$$

3.2. Prospect Theory

Compared with the expected utility theory, the prospect theory proposed by Kahneman and Tversky [32] reveals the irrationality of DMs due to their psychological and behavioral characters in the actual decision-making process, especially under the fuzzy environment. To be specific, the prospect theory indicates the DMs' different risk attitudes based on the reference point. Then, the value function $V(\Delta x_{ij})_{m\times n}$ that reflects the behavioral and psychological characteristics of DMs can be described as follows:

$$V(\Delta x_{ij})_{(m\times n)} = \begin{cases} \left(b_{ij}-\overline{b_j}\right)^{\alpha}, b_{ij} \geq \overline{b_j} \\ -\gamma\left(\overline{b_j}-b_{ij}\right)^{\beta}, b_{ij} < \overline{b_j} \end{cases}$$

where Δx_{ij} represents the deviation between b_{ij} and the reference point $\overline{b_j}$. Considering the different risk preferences towards gains and losses, the parameters of α and β are defined as the risk sensitivity coefficient which meet $\alpha, \beta \in (0, 1)$. It indicates the convexity and concavity of the value function of prospect theory. Besides, the parameter γ $(\gamma > 1)$ shows the risk loss aversion degree of DMs. Based on experiment validation, Kahneman and Tversky [32] provided the value of parameters as $\alpha = \beta = 0.88$, $\gamma = 2.25$.

4. The Proposed Picture Fuzzy Decision System Framework

To achieve the aim of risk evaluation of the consumer trust project, this section proposes an integrated risk evaluation framework by using CRITIC and PT-ARAS methods under the picture fuzzy environment described in Figure 1. The proposed evaluation framework consists of three phases, which can be explained as follows.

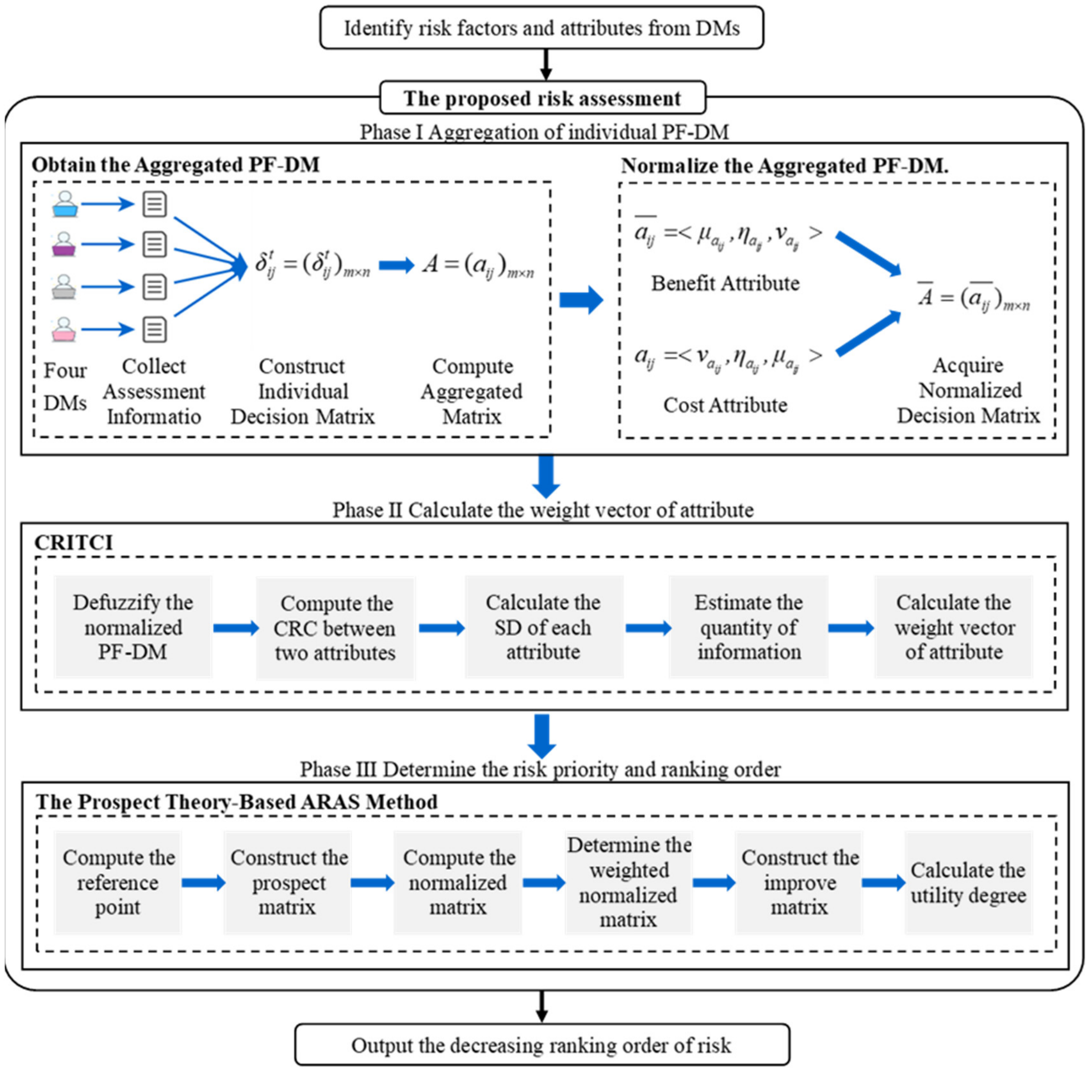

Figure 1. Flowchart of the propounded picture fuzzy decision system framework.

4.1. Phase I: Obtain Picture Fuzzy Decision Matrix (PF-DM)

In the risk evaluation problem, the involved basic elements are stated as below: $P = \{ P_i | i = 1, 2, \cdots, m\}$ denotes the set of risk factors, $C = \{ C_j | j = 1, 2, \cdots, n\}$ indicates the set of risk criteria, and the weight of each criterion is denoted as ω_j, satisfying $\omega_j \in [0, 1]$ and $\sum_{j=1}^{n} \omega_j = 1$. Simultaneously, $E = \{ E_t | t = 1, 2, \cdots, l\}$ represents the experts and the weights of experts are denoted as λ_t, meeting $\lambda_t \in [0, 1]$ and $\sum_{t=1}^{l} \lambda_t = 1$. In the following, the detailed decision steps of the proposed evaluation framework are illustrated.

Step 1: Construct individual PF-DM.

Let $\delta^t = \left(\delta^t{}_{ij}\right)_{m \times n}$ represent the PF-DM of each expert, where ${\delta_{ij}}^t$ means the preference value of P_i under the criteria C_j assessed by the t^{th} expert.

Step 2: Determine the weight information of expert.

Assume that experts' weights are denoted as the linguistic variables and shifted as PFNs. Let $A_t = \langle \mu_t, \eta_t, \nu_t \rangle$ be a PFN for t^{th} expert, then the weight of each expert is computed by

$$\lambda_t = \frac{S(A_t)}{\sum_{t=1}^{l} S(A_t)} \tag{5}$$

where $S(A_t)$ be the score value of PFN A_t.

Step 3: Compute the aggregated PF-DM

$$\begin{aligned} a_{ij} &= PFWA_W(\delta_{ij}{}^1, \delta_{ij}{}^2, \cdots, \delta_{ij}{}^l) \\ &= \left\langle 1 - \prod_{t=1}^{l}\left(1-\mu_{\delta_{ij}}^t\right)^{\lambda_t}, \prod_{t=1}^{l}\left(\eta_{\delta_{ij}}^t\right)^{\lambda_t}, \prod_{t=1}^{l}\left(\nu_{\delta_{ij}}^t + \eta_{\delta_{ij}}^t\right)^{\lambda_t} - \prod_{t=1}^{l}\left(\eta_{\delta_{ij}}^t\right)^{\lambda_t} \right\rangle. \end{aligned} \tag{6}$$

Step 4: Acquire the normalized PF-DM $\overline{A} = \left(\overline{a_{ij}}\right)_{m\times n}$ by

$$\overline{A} = \left(\overline{a_{ij}}\right)_{m\times n} = \begin{cases} \left\langle \mu_{a_{ij}}, \eta_{a_{ij}}, \nu_{a_{ij}} \right\rangle, for \text{ benefit } criterion \\ \left\langle \nu_{a_{ij}}, \eta_{a_{ij}}, \mu_{a_{ij}} \right\rangle, for \text{ cost } criterion \end{cases}. \tag{7}$$

4.2. Phase II: Determine the Weight of Criteria

CRITIC is an objective weight determining method which was developed by Diakoulaki et al. [66]. The detailed computation steps based on the above normalized PF-DM are described as below.

Step 1: Defuzzify the normalized PF-DM by using score function, displayed as:

$$S\left(\overline{a_{ij}}\right) = \frac{\left(1 + \mu_{\overline{a_{ij}}} - \nu_{\overline{a_{ij}}}\right)}{2}. \tag{8}$$

Step 2: Compute the correlation coefficient (CRC) between criteria C_j and C_k

$$\tau_{jk} = \frac{\sum_{i=1}^{m}\left(S\left(\overline{a_{ij}}\right) - \frac{\sum_{i=1}^{m} S\left(\overline{a_{ij}}\right)}{m}\right)\left(S\left(\overline{a_{ik}}\right) - \frac{\sum_{i=1}^{m} S\left(\overline{a_{ik}}\right)}{m}\right)}{\sqrt{\sum_{i=1}^{m}\left(S\left(\overline{a_{ij}}\right) - \frac{\sum_{i=1}^{m} S\left(\overline{a_{ij}}\right)}{m}\right)^2}\sqrt{\sum_{i=1}^{m}\left(S\left(\overline{a_{ik}}\right) - \frac{\sum_{i=1}^{m} S\left(\overline{a_{ik}}\right)}{m}\right)^2}}, k = 1, 2, \cdots, n. \tag{9}$$

Step 3: Compute the standard deviation (SD) of each criterion by

$$SD_j = \sqrt{\frac{\sum_{i=1}^{m}\left(S\left(\overline{a_{ij}}\right) - \frac{\sum_{i=1}^{m} S\left(\overline{a_{ij}}\right)}{m}\right)}{m}}. \tag{10}$$

Step 4: Estimate the quantity of information of each criterion by

$$I_j = SD_j \sum_{k=1}^{n}\left(1 - \tau_{jk}\right). \tag{11}$$

Step 5: Calculate the weight vector of each criterion by

$$\omega_j = \frac{I_j}{\sum_{j=1}^{n} I_j}. \tag{12}$$

4.3. Phase III: Determine Risk Priority and Ranking Order

In this phase, an extended decision-making method is proposed by combining PT and the ARAS method to determine the priority and ranking of risk factors. The steps of the presented PT-ARAS method are illustrated as follows.

Step 1: Based on Equation (3), choose and calculate the reference point $\overline{C_j}$ for all criteria based on the obtained normalized PF-DM $\overline{A} = \left(\overline{a_{ij}}\right)_{m\times n}$:

$$\overline{A_j} = \frac{1}{m}\overset{m}{\underset{i=1}{\oplus}}\overline{a_{ij}} = \left\langle 1-\prod_{i=1}^{m}\left(1-\mu_{\overline{a_{ij}}}\right)^{\frac{1}{m}}, \prod_{i=1}^{m}\left(\eta_{\overline{a_{ij}}}\right)^{\frac{1}{m}}, \prod_{i=1}^{m}\left(\nu_{\overline{a_{ij}}}+\eta_{\overline{a_{ij}}}\right)^{\frac{1}{m}} - \prod_{i=1}^{m}\eta_{\overline{a_{ij}}}^{\frac{1}{m}}\right\rangle \quad (13)$$

where the reference point $\overline{A_j}$ represents the mean value of all criteria which is also used in existing literature [91,92].

Step 2: Construct the prospect matrix $V = (v_{ij})_{m\times n}$

$$V = (v_{ij})_{(m\times n)} = \begin{cases} \left(d\left(\overline{a_{ij}},\overline{a_j}\right)\right)^{\alpha},\ S\left(\overline{a_{ij}}\right) \geq S\left(\overline{a_j}\right) \\ -\gamma\left(d\left(\overline{a_{ij}},\overline{a_j}\right)\right)^{\beta},\ S\left(\overline{a_{ij}}\right) < S\left(\overline{a_j}\right) \end{cases} \quad (14)$$

where the score value $S(\bullet)$ is calculated by Equation (1) to compare the score of two PFNs. Moreover, the deviation between the prospect value and the reference point under the picture fuzzy environment can be calculated by distance measure $d\left(\overline{a_{ij}},\overline{a_j}\right)$, which demonstrates either positive or negative deviation between the $\overline{a_{ij}}$ and reference point $\overline{a_j}$. Meanwhile, v_{ij} denotes the prospect value of the i^{th} risk factor under the j^{th} criteria.

Step 3: Calculate the normalized prospect matrix $\overline{V} = \left(\overline{v_{ij}}\right)_{m\times n}$:

$$\overline{V} = \left(\overline{v_{ij}}\right)_{m\times n} = \begin{cases} \frac{v_{ij}-Minv_{ij}}{Maxv_{ij}-Minv_{ij}}, for\ the\ benefit\ criterion \\ \frac{Maxv_{ij}-v_{ij}}{Maxv_{ij}-Minv_{ij}}, for\ the\ \text{cost}\ criterion \end{cases}. \quad (15)$$

Step 4: Determine the weighed normalized matrix $\hat{V} = \left(\hat{v_{ij}}\right)_{m\times n}$:

$$\hat{V} = \left(\hat{v_{ij}}\right)_{m\times n} = \overline{v_{ij}} \times \omega_j \quad (16)$$

where ω_j represents the criteria weight obtained in Phase II.

Step 5: Construct the improved prospect matrix:

$$\hat{V} = \left(\hat{v_{ij}}\right)_{(m+1)\times n} = \begin{pmatrix} \hat{v_{01}} & \hat{v_{02}} & \cdots & \hat{v_{0n}} \\ \hat{v_{11}} & \hat{v_{12}} & \cdots & \hat{v_{1n}} \\ \vdots & \vdots & \ddots & \vdots \\ \hat{v_{m1}} & \hat{v_{m2}} & \cdots & \hat{v_{mn}} \end{pmatrix} \quad (17)$$

where $\hat{v_{0j}}$ is denoted the optimal value of j^{th} criteria and computed by

$$\hat{v_{0j}} = \begin{cases} Max\hat{v_{ij}}, for\ the\ \text{benefit}\ criterion \\ Min\hat{v_{ij}}, for\ the\ \text{cost}\ criterion \end{cases}.$$

Step 6: Calculate the values of the optimal function V_i and utility degree Q_i:

$$V_i = \sum_{j=1}^{n}\hat{v_{ij}} \quad (18)$$

Step 7: Rank the risk factors in descending order according to the values of V_i.

5. Case Study

In this section, based on the constructed risk evaluation model for the consumer trust project, the PT-CRITIC-ARAS methods concerned with risk preference and irrationality of DMs are implemented in a specific consumer trust project, and the results and discussions are shown at the same time. Moreover, the sensitivity analysis and comparative analysis are given to demonstrate the feasibility and necessity of the introduced methodology.

5.1. Problem Description and Establishment of Risk Evaluation Model

In recent years, the release of the "New asset Management Regulations" brings stricter regulations from the regulatory authorities onto the asset management industry. Meanwhile, coupled with China's economic slowdown, the financial industry, especially the trust industry, has been hit by unprecedented damage, such as the frequent appearance of redemption dilemmas of traditional trust products. It is urgent for Chinese trust companies to expand the innovative to achieve the transformation and upgrading of traditional business. Consumer financial trust, as an innovative business form, has attracted wide attention for the trust industry while meeting consumption and financial needs simultaneously. Under this background, risk management to improve the capacities of risk resilience so as to ensure the smooth implementation of this innovative business for the whole industry has great practical significance. Company Z, which holds the leading position among integrated financial service providers in China, for the past few years, has allowed consumer finance to become the main business that occupies the company's attention. By 2020, Company Z, which acts as the trustee, has instituted the RS consumer trust project by cooperating with the leasing company. In the RS project, besides the trust Company Z (trustee), others, including the principal, guarantor, counterparty, and charterer, also play an indispensable role. However, the characteristics of multiple subjects will inevitably increase the complexity and uncertainty of such a project. Therefore, risk management by effectively evaluating the priority of risks has become particularly important for the steady and healthy development of this innovative business.

Initially, the establishment of an evaluation index system is crucial to evaluating the risk priority of the consumer trust project. With reference to the discussion of China Trust company's risk factors by Zhu and Yang [93], sources of risks in the consumer trust project can be roughly divided into internal and external dimensions. On this basis, considering the multi-stage and multi-subject characteristics of such a project, as well as existing literature [94,95], twenty-two common risks concretely identified from three internal and three external dimensions means that six sources are denoted as Rij (means the j^{th} risk under the i^{th} source) and shown in Table 1. Among them, internal risks are identified from three stages of project implementation by considering the role and behavior of each participant, respectively. To be specific, during the project investigation (S1), approval (S2), and redemption (S3), sixteen internal risks are selected in this paper. Among them, six internal risks existed in project investigation (S1), which can be denoted as R11, R12, and R13, and project approval (S2), which can be denoted as R21, R22, and R23, all derived from Company Z. Discriminately, in project redemption (S3), there are ten internal risks which are not only caused by the trustee (trust company) itself but also the principal, counterparty, guarantor, and charterer. Due to the ten risk factors in this stage, considering the tidiness of the numbering of risks, the letter j starts at 0 instead of 1. Moreover, the six external risks which will run through the whole process of project implementation were systematically determined from social (S4), legal and policy (S5), and economic aspect (S6).

Subsequently, after determining the risk evaluation index system, the establishment of the risk evaluation model still leaves the selection of criteria. In previous research, the criteria used for risk evaluation involved only risk impact and risk probability of occurrence. However, as the extension of the risk concept, only two criteria may not be sufficient to describe all aspects of the risks [12]. Later, Ebrahimnejad et al. [96] added three criteria, namely, quickness of reaction, event measure quantity, and the ability for risk in construction projects. Yazdani-Chamzini et al. [97] developed four criteria, including risk impact, likelihood, uncertainty, and response ability. Wang et al. [12] selected probability, impact, exposure, and response capacity as principles by which to evaluate risk in energy performance contracting projects. Further, Wang et al. [14] enriched the risk criteria into impact, probability, unpredictability, and risk urgency. Recently, Ilbahar et al. [29] prioritized risks by analyzing probability, severity, and detectability. Finally, according to the actual situation of RS consumer trust project and experts' opinions, four criteria (C1–C4) selected from the above literature to assess risks are shown in Table 2.

Table 1. Risk evaluation index system of consumer trust project.

Dimension	Source	Risk
Internal risks	Investigation stage (S1)	Judgment of Information (R11) Normalization of Implementation (R12) Rationality of Analysis (R13)
	Approval stage (S2)	Identification of Project (R21) Transaction Structure Design (R22) Risk Control and Management (R23)
	Redemption stage (S3)	Principals' Investment Aspiration (R30) Counterparties' Finance (R31) Counterparties' Contract Fulfillment (R32) Counterparties' Technology (R33) Guarantors' Finance (R34) Guarantors' Credit (R35) Charterers' Consuming Intention (R36) Charterers' Fraud (R37) Charterers' Moral (R38) Charterers' Credit (R39)
External risks	Social aspect (S4)	Consumer Market Change (R41) Guidance of Public Opinion (R42)
	Legal and Policy aspect (S5)	Legality and compliance (R51) Policy Changes (R52)
	Economic aspect (S6)	Regional Economic Fluctuation (R61) Macroeconomic Changes (R62)

Table 2. Risk criteria and their explanations.

Criteria	Explanation
Probability of occurrence	It represents the likelihood of risk occurrence.
Risk impact	It means the impact when risk occurs.
Risk detectability	It shows the probability to detect risk.
Risk responsiveness	It indicates the degree of reaction when risk occurs.

Ultimately, the hierarchical structure of the consumer trust project evaluation problem is established in Figure 2. As can be noticed in Figure 2, the risk evaluation model consists of 4 risk criteria, 16 internal risks, and 6 external risks. Based on the above analysis and discussions, the problem of the risk evaluation of consumer trust projects could be regarded as a classic multiple criteria decision-making issue [4].

5.2. Operational Results

In this subsection, the proposed picture fuzzy decision system framework is implemented to obtain the risks priority and ranking order which is listed in the established risk evaluation index system in Figure 2. Before that, to evaluate risks in such an innovative business, four experts with an average of 16 years of experience are selected by Company Z to participate in this case study. These experts are professionals who, respectively, are working as department managing director, trust manager, RS project manager, and RS operation manager. Therefore, they hold managerial positions to directly influence the risk evaluation of the RS project. Interviews were carried out with them to collect linguistic evaluations considering criteria and risks. According to the linguistic scale for proficiency defined in Table 3 (adapted from [31]), the assessment of expert's weight based on the levels of technical knowledge and expertise and the result of each expert calculated by Equation (4) are listed in Table 4. Therefore, the proposed picture fuzzy decision system framework is implemented in this research as follows.

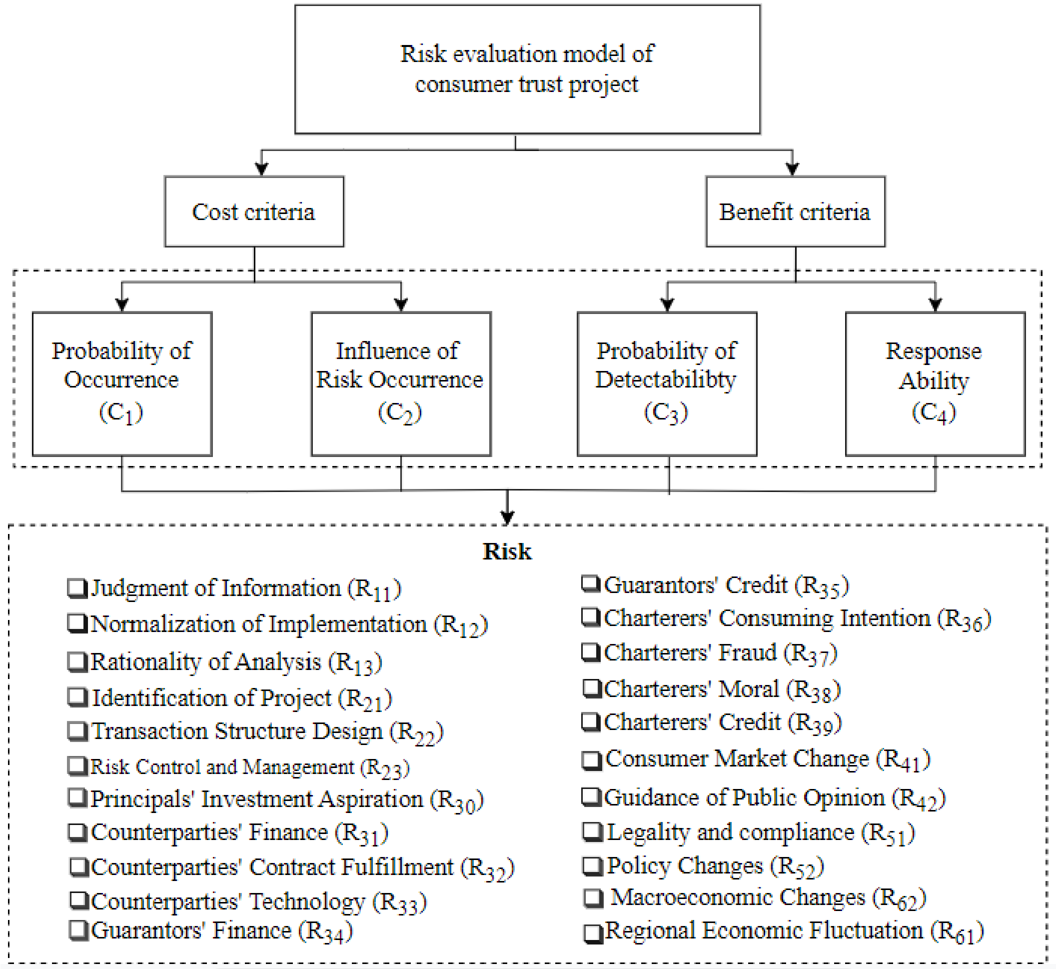

Figure 2. The risk evaluation model of consumer trust project.

Table 3. Linguistic scales for proficiency and rating.

Linguistic Scale for Proficiency	Picture Fuzzy Numbers (PFNs)	Linguistic Scale for Rating
Very Poor (VP)	$\langle 0.1, 0.00, 0.85 \rangle$	Very Low (VL)
Poor (P)	$\langle 0.25, 0.05, 0.6 \rangle$	Low (L)
Moderately Poor (MP)	$\langle 0.3, 0.00, 0.6 \rangle$	Moderately Low (ML)
Fair (F)	$\langle 0.5, 0.1, 0.4 \rangle$	Fair (F)
Moderately Good (MG)	$\langle 0.6, 0.0, 0.3 \rangle$	Moderately High (MH)
Good (G)	$\langle 0.75, 0.05, 0.1 \rangle$	High (H)
Very Good (VG)	$\langle 0.9, 0.00, 0.05 \rangle$	Very High (VH)

Table 4. Experts' weights for assessing risk factors.

	Expert 1	Expert 2	Expert 3	Expert 4
Linguistic rating	VG	G	MP	MG
(PFNs)	$\langle 0.9, 0.00, 0.05 \rangle$	$\langle 0.75, 0.05, 0.1 \rangle$	$\langle 0.5, 0.1, 0.4 \rangle$	$\langle 0.6, 0.0, 0.3 \rangle$
Weight	0.31	0.28	0.19	0.22

In phase I, according to the linguistic scale for rating defined in Table 3, the evaluation information of internal and external risks under all criteria from experts can be obtained in Tables 5 and 6. Moreover, based on the obtained linguistic evaluation decision matrix, we use Table 3 to translate the linguistic ratings information into picture fuzzy numbers by the picture fuzzy scale. According to the experts' weights, the aggregated evaluation matrix can be obtained by utilizing Equation (5). Then, considering C1 and C2 belong to the cost criteria, Equation (6) is used to normalize the aggregated evaluation matrix, which can be obtained in Tables 7 and 8.

Table 5. Linguistic ratings of internal risk factors from four DMs.

Internal Risk	C1	C2	C3	C4
R11	(L, L, L, ML)	(ML, ML, MH, F)	(F, H, MH, H)	(ML, F, F, F)
R12	(F, ML, F, ML)	(MH, H, MH, H)	(H, H, MH, H)	(MH, H, MH, H)
R13	(ML, MH, F, MH)	(MH, F, F, MH)	(H, ML, F, MH)	(F, ML, MH, ML)
R21	(F, F, MH, F)	(F, H, H, H)	(MH, H, H, H)	(ML, F, H, H)
R22	(ML, F, L, F)	(L, VH, MH, VH)	(MH, H, H, H)	(F, MH, MH, MH)
R23	(ML, ML, ML, ML)	(MH, H, H, H)	(F, VH, H, H)	(F, ML, H, F)
R30	(F, ML, L, ML)	(F, F, L, ML)	(H, VH, MH, VH)	(ML, F, MH, F)
R31	(F, F, F, F)	(F, L, ML, VL)	(L, VL, VL, VL)	(F, MH, MH, ML)
R32	(F, F, F, F)	(ML, MH, MH, H)	(VH, VH, MH, H)	(L, ML, H, ML)
R33	(F, MH, F, MH)	(ML, MH, H, F)	(H, MH, H, H)	(MH, MH, H, MH)
R34	(F, VH, P, VH)	(F, MH, MH, MH)	(MH, H, H, H)	(F, H, H, H)
R35	(ML, H, MH, H)	(ML, MH, MH, F)	(MH, H, H, H)	(F, MH, H, MH)
R36	(F, F, F, F)	(MH, MH, MH, MH)	(MH, MH, F, H)	(ML, H, F, H)
R37	(F, MH, F, MH)	(ML, ML, F, F)	(MH, VH, VH, VH)	(ML, F, F, F)
R38	(F, MH, F, MH)	(L, ML, F, F)	(MH, H, H, VH)	(ML, H, MH, H)
R39	(MH, F, MH, F)	(H, VH, H, H)	(MH, H, H, H)	(MH, H, H, MH)

Table 6. Linguistic ratings of external risk factors from four DMs.

External Risk	C1	C2	C3	C4
R41	(ML, F, L, ML)	(F, F, MH, F)	(H, MH, MH, F)	(L, H, MH, H)
R42	(ML, F, VL, ML)	(MH, MH, VL, MH)	(MH, MH, L, F)	(F, ML, MH, ML)
R51	(ML, ML, F, ML)	(H, VH, VH, VH)	(VH, VH, VH, VH)	(F, VH, VH, H)
R52	(ML, ML, ML, ML)	(VH, VH, VH, VH)	(VH, VH, VH, VH)	(F, MH, MH, H)
R61	(L, F, ML, F)	(H, H, VH, F)	(MH, H, MH, H)	(L, VH, VH, VH)
R62	(ML, ML, F, ML)	(H, H, VH, VH)	(H, H, VH, H)	(ML, H, H, H)

Table 7. Aggregated picture fuzzy assessment matrix for internal risk.

Internal Risk	C1	C2	C3	C4
R11	$\langle 0.26, 0.00, 0.64 \rangle$	$\langle 0.51, 0.00, 0.42 \rangle$	$\langle 0.66, 0.00, 0.25 \rangle$	$\langle 0.53, 0.00, 0.45 \rangle$
R12	$\langle 0.41, 0.00, 0.55 \rangle$	$\langle 0.21, 0.00, 0.68 \rangle$	$\langle 0.73, 0.00, 0.17 \rangle$	$\langle 0.21, 0.00, 0.68 \rangle$
R13	$\langle 0.50, 0.00, 0.41 \rangle$	$\langle 0.47, 0.00, 0.47 \rangle$	$\langle 0.58, 0.00, 0.32 \rangle$	$\langle 0.50, 0.00, 0.43 \rangle$
R21	$\langle 0.52, 0.00, 0.45 \rangle$	$\langle 0.16, 0.06, 0.69 \rangle$	$\langle 0.71, 0.00, 0.19 \rangle$	$\langle 0.32, 0.00, 0.58 \rangle$
R22	$\langle 0.40, 0.00, 0.56 \rangle$	$\langle 0.16, 0.00, 0.76 \rangle$	$\langle 0.71, 0.00, 0.19 \rangle$	$\langle 0.35, 0.00, 0.57 \rangle$
R23	$\langle 0.30, 0.00, 0.60 \rangle$	$\langle 0.19, 0.00, 0.71 \rangle$	$\langle 0.76, 0.00, 0.16 \rangle$	$\langle 0.42, 0.00, 0.52 \rangle$
R30	$\langle 0.36, 0.00, 0.58 \rangle$	$\langle 0.55, 0.00, 0.42 \rangle$	$\langle 0.83, 0.00, 0.10 \rangle$	$\langle 0.48, 0.00, 0.47 \rangle$
R31	$\langle 0.50, 0.10, 0.40 \rangle$	$\langle 0.20, 0.00, 0.72 \rangle$	$\langle 0.87, 0.00, 0.07 \rangle$	$\langle 0.41, 0.00, 0.52 \rangle$
R32	$\langle 0.50, 0.10, 0.40 \rangle$	$\langle 0.32, 0.00, 0.57 \rangle$	$\langle 0.84, 0.00, 0.09 \rangle$	$\langle 0.47, 0.00, 0.41 \rangle$
R33	$\langle 0.55, 0.00, 0.39 \rangle$	$\langle 0.36, 0.00, 0.54 \rangle$	$\langle 0.71, 0.00, 0.18 \rangle$	$\langle 0.26, 0.00, 0.63 \rangle$
R34	$\langle 0.76, 0.00, 0.17 \rangle$	$\langle 0.35, 0.00, 0.57 \rangle$	$\langle 0.71, 0.00, 0.19 \rangle$	$\langle 0.16, 0.06, 0.69 \rangle$
R35	$\langle 0.62, 0.00, 0.26 \rangle$	$\langle 0.42, 0.00, 0.50 \rangle$	$\langle 0.67, 0.00, 0.23 \rangle$	$\langle 0.31, 0.00, 0.61 \rangle$
R36	$\langle 0.50, 0.10, 0.40 \rangle$	$\langle 0.37, 0.00, 0.52 \rangle$	$\langle 0.62, 0.00, 0.28 \rangle$	$\langle 0.29, 0.00, 0.61 \rangle$
R37	$\langle 0.55, 0.00, 0.39 \rangle$	$\langle 0.56, 0.00, 0.39 \rangle$	$\langle 0.85, 0.00, 0.09 \rangle$	$\langle 0.53, 0.00, 0.45 \rangle$
R38	$\langle 0.55, 0.00, 0.39 \rangle$	$\langle 0.57, 0.00, 0.38 \rangle$	$\langle 0.76, 0.00, 0.15 \rangle$	$\langle 0.26, 0.00, 0.62 \rangle$
R39	$\langle 0.55, 0.00, 0.39 \rangle$	$\langle 0.11, 0.00, 0.81 \rangle$	$\langle 0.71, 0.00, 0.19 \rangle$	$\langle 0.22, 0.00, 0.68 \rangle$

Table 8. Aggregated picture fuzzy assessment matrix for external risk.

External Risk	C1	C2	C3	C4
R41	$\langle 0.35, 0.00, 0.58\rangle$	$\langle 0.48, 0.00, 0.47\rangle$	$\langle 0.64, 0.00, 0.27\rangle$	$\langle 0.27, 0.00, 0.62\rangle$
R42	$\langle 0.33, 0.00, 0.61\rangle$	$\langle 0.30, 0.00, 0.59\rangle$	$\langle 0.53, 0.00, 0.39\rangle$	$\langle 0.50, 0.00, 0.43\rangle$
R51	$\langle 0.34, 0.00, 0.58\rangle$	$\langle 0.13, 0.00, 0.79\rangle$	$\langle 0.90, 0.00, 0.05\rangle$	$\langle 0.13, 0.00, 0.80\rangle$
R52	$\langle 0.30, 0.00, 0.60\rangle$	$\langle 0.07, 0.00, 0.87\rangle$	$\langle 0.90, 0.00, 0.05\rangle$	$\langle 0.30, 0.00, 0.61\rangle$
R61	$\langle 0.40, 0.00, 0.56\rangle$	$\langle 0.12, 0.00, 0.81\rangle$	$\langle 0.68, 0.00, 0.21\rangle$	$\langle 0.11, 0.00, 0.81\rangle$
R62	$\langle 0.30, 0.00, 0.60\rangle$	$\langle 0.10, 0.00, 0.83\rangle$	$\langle 0.79, 0.00, 0.12\rangle$	$\langle 0.23, 0.00, 0.66\rangle$

In phase II, according to the CRITIC method, the CRC, SD, and the criteria weight are estimated based on Equations (8)–(12) and portrayed in Table 9. As shown in Table 9, risk impact (0.28) is the most significant criteria, and risk detectability (0.23) is the least important criteria. In addition, the weight of probability of occurrence (0.25) is higher than risk responsiveness (0.24).

Table 9. SD, CRC, and criteria weight.

	CRC				SD	Weight
	C1	C2	C3	C4		
C1	1.000	0.279	−0.033	−0.128	0.12	0.25
C2	0.279	1.000	−0.286	0.511	0.16	0.28
C3	−0.0329	−0.2864	1.0000	−0.1491	0.09	0.23
C4	−0.1275	0.5109	−0.1491	1.0000	0.12	0.24

Finally, in phase III, the risk priorities are ranked by applying the extended ARAS approach. Initially, the reference point in the proposed framework chosen by the four experts in Company Z is the mean value for all criteria. Therefore, based on the normalized matrix in Tables 7 and 8 and the Equation (3), the reference points of four criteria under picture fuzzy environment can be calculated as

$$\overline{C_j} = (\langle 0.46, 0.00, 0.47\rangle, \langle 0.32, 0.00, 0.60\rangle, \langle 0.76, 0.00, 0.16\rangle, \langle 0.34, 0.00, 0.58\rangle\ )$$

Then, the prospect value matrix and the normalized weighed prospect value matrix are acquired by Equations (14)–(16). Next, based on Equation (16), the optimal prospect value of all criteria in crisp value are described as $\hat{v_{0j}} = (0.25, 0.00, 0.23, 0.00)$. Finally, we rank the priority of all risks by calculating the alternative utility using Equations (17)–(18) in descending order is acquired, as follows:

$$R_{51} \succ R_{39} \succ R_{61} \succ R_{34} \succ R_{52} \succ R_{31} \succ R_{62} \succ R_{21} \succ R_{12} \succ R_{33} \succ R_{22}$$
$$\succ R_{38} \succ R_{32} \succ R_{35} \succ R_{23} \succ R_{36} \succ R_{37} \succ R_{30} \succ R_{41} \succ R_{13} \succ R_{42} \succ R_{11}$$

In summary, legality and compliance risk (R_{51}) and charterers' Credit (R_{39}) risk were ranked first and second. To be specific, the external risk of legality and compliance, yielded from the relevant supervisor as the highest external risk, directly impacts the operational environment and increases the uncertainty for trust projects. In addition, the internal risk of charterers' credit, with the second priority, may increase the risks in project redemption so as to affect the overdue rate of the RS project.

5.3. Sensitivity Analysis

In the practical decision-making process, DM's risk attitude has cased perceptible influence on decision-making results according to Xu et al. [98]. The parameter γ is utilized to describe the degree of risk loss aversion which indicates the sensitivity to loss. The larger the value of γ, the higher the sensitivity to loss. According to Kahneman and Tversky [32], $\gamma = 0.88$ is more consistent with the actual situation. To explore the impact of loss aversion coefficient variation γ on ranking order and risk priority, this paper implements a sensitivity analysis by altering the parameter γ in different values from 1 to 3 through the following experiments. The corresponding results of the priority and ranking order of each risk obtained with different γ are shown in Figure 3 and Table 10.

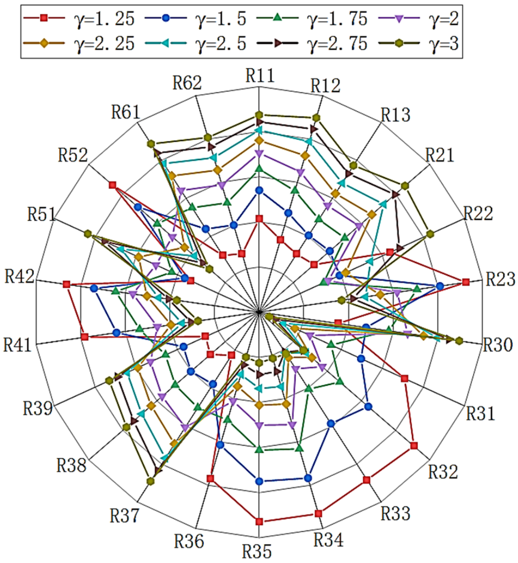

Figure 3. Priority of each risk obtained with different values of γ.

Table 10. Ranking orders obtained for different values of γ.

	γ = 1	γ = 1.25	γ = 1.5	γ = 1.75	γ = 2	γ = 2.25	γ = 2.5	γ = 2.75	γ = 3
R_{11}	22	22	22	22	22	22	22	22	22
R_{12}	9	9	9	9	9	9	9	9	9
R_{13}	20	20	20	20	20	20	20	20	20
R_{21}	8	8	8	8	8	8	8	8	8
R_{22}	11	11	11	11	11	11	12	12	12
R_{23}	16	15	15	15	15	15	15	15	15
R_{30}	19	19	19	19	18	18	18	18	18
R_{31}	5	6	6	6	6	6	6	6	6
R_{32}	13	13	12	13	13	13	13	13	13
R_{33}	10	10	10	10	10	10	10	10	10
R_{34}	3	3	3	4	4	4	4	4	4
R_{35}	12	12	13	14	14	14	14	14	14
R_{36}	15	16	16	16	16	16	16	16	17
R_{37}	17	17	17	17	17	17	17	17	16
R_{38}	14	14	14	12	12	12	11	11	11
R_{39}	2	2	2	2	2	2	2	2	2
R_{41}	18	18	18	18	19	19	19	19	19
R_{42}	21	21	21	21	21	21	21	21	21
R_{51}	1	1	1	1	1	1	1	1	1
R_{52}	4	5	5	5	5	5	5	5	5
R_{61}	6	4	4	3	3	3	3	3	3
R_{62}	7	7	7	7	7	7	7	7	7

As shown in Figure 3, it can be found that the priority results of 22 risk factors present are obviously sensitive to the parameter γ. Meanwhile, as shown in Table 10, it is obvious that the rank of highest priorities, R_{51} and R_{39}, and lowest priorities, R_{42} and R_{11}, are stable when the priorities of these risks are changed with the increasing parameter γ. Similarly, the ranking orders of R_{11}, R_{13}, R_{21}, R_{32}, R_{33}also remain unchanged. In addition, the priorities and ranking orders of other risks are influenced by the changing coefficient of risk loss aversion. These results mean that the ranking order and priority of each risk are sensitive to the value of the risk loss aversion coefficient γ. In other words, it highlights that the DMs can choose different values of γ according to the risk preference to obtain an ideal risk sequence in the proposed evaluation framework.

5.4. Comparative Analysis

To prove the necessity and validity of the proposed integrated framework, the following measures, including the comparison with the traditional ARAS, PFWA operator, and the PT-MABAC method extended by Wang et al. [12], are conducted. The final ranking results yielded by the above three methods and the proposed framework with the case study in our paper are shown in Figure 4. It can be found that ranking orders obtained by the proposed method and the PT-MABAC method are of high similarity, which are obviously different from those obtained by the other two methods.

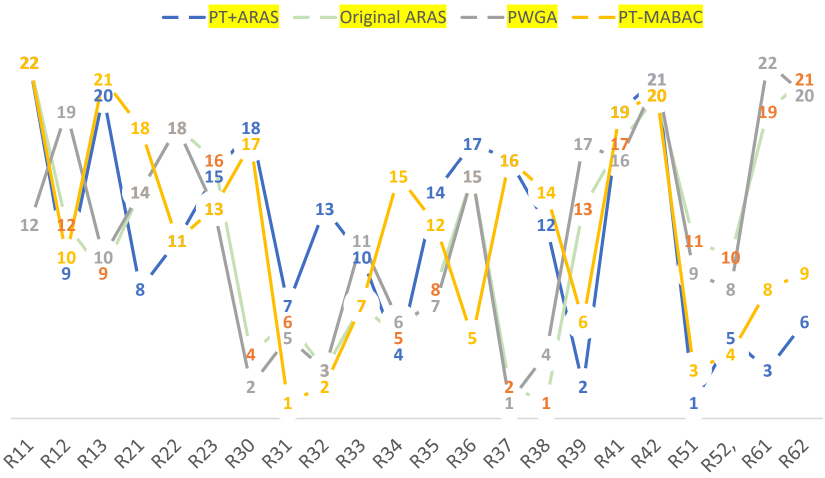

Figure 4. Ranking orders of 22 risks with different approaches.

Further, considering discrepant ranking results obtained by using different decision-making approaches, Spearman's rank-correction test, proposed by Parkan and Wu [99], is used to ascertain whether there is a significant rank-correlation between two sets of ranking. The comparative results and Spearman's correlation, calculated by the above methods, are listed in Table 11. From the comparison results presented in Table 11, it can be observed that the rank orders are significantly different. In addition, the difference is derived from discriminatory decision theories applied in two types of method. Meanwhile, the ranking orders of the proposed PT-ARAS method and the PT-MABAC method have a strong positive correlation. In summary, the proposed method is feasible and effective in treating complex uncertain risk decision problems.

Table 11. Ranking results and Spearman's correlation of four methods.

Ranking				Ranking Difference					
TH-ARAS (Method1)	**PFN-ARAS (Method2)**	**PWAG (Method3)**	**TH + MABAC (Method4)**	**1 vs. 2**	**1 vs. 3**	**1 vs. 4**	**2 vs. 3**	**2 vs. 4**	**3 vs. 4**
22	12	12	22	100	100	0	0	100	100
9	19	19	10	100	100	1	0	81	81
20	10	10	21	100	100	1	0	121	121
8	13	14	18	25	36	100	1	25	16
11	18	18	11	49	49	0	0	49	49
15	14	13	13	1	4	4	1	1	0
18	2	2	17	256	256	1	0	225	225
7	6	5	1	1	4	36	1	25	16
13	3	3	2	100	100	121	0	1	1
10	11	11	7	1	1	9	0	16	16
4	5	6	15	1	4	121	1	100	81
14	7	7	12	49	49	4	0	25	25
17	15	15	5	4	4	144	0	100	100
16	1	1	16	225	225	0	0	225	225
12	4	4	14	64	64	4	0	100	100
2	17	17	6	225	225	16	0	121	121
19	16	16	19	9	9	0	0	9	9
21	21	21	20	0	0	1	0	1	1
1	9	9	3	64	64	4	0	36	36
5	8	8	4	9	9	1	0	16	16
3	22	22	8	361	361	25	0	196	196
6	20	20	9	196	196	9	0	121	121
		RC		0.095	0.106	0.682	0.998	0.043	0.065
		Z		0.437	0.484	3.025	4.572	0.199	0.298

6. Conclusions

The trust company, as an important part of the Chinese shadow banking system, while bringing economic benefits, also causes significant financial risks. Risks have adverse effects on the profitability and competitiveness of the trust industry. Properly, the impact of potential risks can be mitigated or even eliminated by determining risk priorities to provide appropriate risk mitigation strategies for the main risks. However, limited literature has used quantitative methods to evaluate risks in trust projects, especially in the innovative business of consumer trust projects. Therefore, this paper was concerned with the determination of risk priority and the ranking order under multiple qualitative criteria in consumer trust projects as an uncertain and ambiguous MCDM problem.

Considering the risk assessment process is generally based on expert judgments, which usually include both fuzziness and bounded rationality bias, the implementation of consumer trust projects might be quite risky due to long-term capital investment cycles with unpredictable benefits. Therefore, in addition to describing experts expressing their views and evaluations on subjective complex factors more effectively and accurately, it is necessary to reflect the risk reference of experts. This research proposed the PT-ARAS framework under the picture fuzzy environment to handle the prioritization and ranking order of risks associated with consumer trust projects. In the proposed framework, the comprehensive risk evaluation model for the consumer trust project consists of a risk evaluation index system, and relevant criteria are initially identified by the literature review and experts. Subsequently, the picture fuzzy numbers are used to describe fuzziness flexibly in decision-making under each criterion evaluated for this project, which can be translated from risk evaluation information described by linguistic ratings obtained from experts. Then, the weight of risk criteria is determined by CRITIC method, which simultaneously considers the conflict and correlation between the two criteria. Furthermore, the traditional ARAS method with the prospect theory is proposed to consider the DM's risk preference. The psychological factors of experts are introduced in the evaluation process, which makes the evaluation results practical. The comparative analysis indicates the theoretical and practical significance of considering bounded rationality and the behavioral psychology of the DM by changing the parameter of the risk aversion coefficient. In addition, the necessity and validity of the proposed method are demonstrated in contrast to traditional picture fuzzy decision methods in the existing literature.

This proposed framework is applicable to the evaluation of risk priority and ranking for consumer trust projects. Further studies could extend the ARAS method into cumulative prospect theory, third-generation prospect theory, and so on. Meanwhile, considering various experts' preferences under different research fields of risk evaluation is also an interesting direction to further strengthen the scientific of the actual risk assessment. In addition, with the rapid development of the digital industry, establishing a more complete trust project risk assessment index system based on digital concepts is also an important research hot spot.

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