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An Online Review Data-Driven Fuzzy Large-Scale Group Decision-Making Method Based on Dual Fine-Tuning

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Abstract: Large-scale group decision-making (LSGDM) involves aggregating the opinions of participating decision-makers into collective opinions and selecting optimal solutions, addressing challenges such as a large number of participants, significant scale, and a low consensus. In real-world scenarios of LSGDM, various challenges are often encountered due to factors such as fuzzy uncertainties in decision information, the large size of decision groups, and the diverse backgrounds of participants. This paper introduces a dual fine-tuning-based LSGDM method using an online review. Initially, the sentiment analysis is conducted on online review data, and the identified sentiment words are graded and quantified into a fuzzy data set to understand the emotional tendencies of the text. Then, the Louvain algorithm is used to cluster the decision-makers. Meanwhile, a method combining Euclidean distances with Wasserstein distances is introduced to accurately measure data similarities and improve clustering performances. During the consensus-reaching process (CRP), a two-stage approach is employed to adjust the scores: to begin with, by refining the scores of the decision representatives via minor-scale group adjustments to generate a score matrix. Then, by identifying the scores corresponding to the minimum consensus level in the matrix for adjustment. Subsequently, the final adjusted score matrix is integrated with the prospect–regret theory to derive the comprehensive brand scores and rankings. Ultimately, the practicality and efficiency of the proposed model are demonstrated using a case study focused on the purchase of solar lamps. In summary, not only does the model effectively extract the online review data and enhance decision efficiency via clustering, but the dual fine-tuning mechanism in the model to improve consensus attainment also reduces the number of adjustment rounds and avoids multiple cycles without achieving the consensus.

Keywords: large-scale group decision-making; dual fine-tuning; online review data; prospect-regret theory; clustering analysis

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1. Introduction

With the development of the digital economy, various online platforms, such as social media, online forums, and e-commerce websites, have become important channels for people to communicate and express opinions widely. The scale of decision members involved in these platforms has expanded continuously. When the scale of decision-makers exceeds a certain threshold, the group decision-making issue can be classified as an LSGDM challenge [1]. Overall, LSGDM has the following three characteristics: first, the decision group is large and diverse in opinions; second, the decision information involved in the process is highly uncertain and ambiguous; third, the participants in decision-making have different backgrounds, interests, and preferences, leading to low consensus and increasing decision complexity. In summary, LSGDM still faces many challenges.

In the sentiment analysis, the large scale of online reviews requires efficient data processing, integrating emotional elements into the LSGDM process. When evaluating options, people express emotions in various ways, such as positive, neutral, and negative emotions.

Therefore, accurately identifying and quantifying these emotional data is crucial. In the social network analysis, trust relationships among decision-makers may potentially influence clustering, opinion collection, and the group consensus process. Due to insufficient understanding of the internal structure of the group and the relationships among members, it is challenging to identify subgroups with similar characteristics or opinions. The clustering analysis is a crucial step in reducing the dimensionality of decision-makers and acquiring objective weight data. Therefore, effective clustering is one of the challenges of LSGDM. In the CRP, the LSGDM leads to a low initial consensus level. For instance, when purchasing solar garden lights, most decision-makers believe that the garden light has a long lighting time. However, some decision-makers think that the lighting time is short. Thus, achieving a high degree of consensus among experts in a single decision-making process is difficult. In summary, this paper intends to explore a dual fine-tuning LSGDM model. The following sections will introduce the current research status and research motivations from three aspects: the sentiment analysis, LSGDM, and behavioral decision-making.

Consumers' purchasing decisions are influenced not only by the attributes and evaluation standards of the products themselves but also by the online reviews and feedback from other consumers. As a result, consumers are now in the habit of looking up the experiences and feedback of prior buyers before making a purchase [2]. Specifically, how to effectively extract and analyze the sentiment factors contained in the review data and then accurately and effectively convert them into preference datasets is a focus of scholars. Preprocessing and the sentiment analysis are particularly important when selecting products, given that numerous online reviews are rich in emotional content and biases. Additionally, decision-makers must take into account various factors, such as price, precision, and convenience [3]. Through the sentiment analysis, insights can be gained into the emotional tendencies and attitudes of group members towards specific topics, issues, or decisions, which is significant for the formulation and implementation of large-scale group decisions. In summary, how to extract realistic decision data from online comments and reasonably depict the fuzzy uncertainty of the data in realistic decision scenarios, which is challenging.

The classic process of LSGDM, according to vertical research ideas, roughly includes clustering decision-makers, determining weights, and reaching a consensus. When dealing with LSGDM problems, integrating members' relationship information using social networks is considered an effective method. Most existing research constructs social networks based on the trust relationships between experts. Studies on social influence theory indicate that there is an interaction between similarity and social relationships, and similarity characteristics influence group relationships [4]. To address the issue of the large scale in the LSGDM, numerous scholars strive to address the LSGDM problems by employing clustering algorithms to reduce dimensions. Clustering algorithms can reduce decision complexity and make decision information among decision-makers within the same cluster more similar. This paper uses the improved Louvain algorithm. Compared with other graph-clustering algorithms, one of the most notable advantages of the Louvain algorithm is its efficiency and scalability; another advantage is its ability to handle weighted graphs, effectively dealing with the community structure division of complex networks while maintaining sound time complexity [5]. These advantages make the Louvain algorithm one of the preferred graph-clustering algorithms in many practical applications, especially in handling large-scale and complex network data. Specifically, the Wasserstein distance considers not only the position of the data points but also the shape and structure of their distribution. It performs well in handling probability distributions or non-continuous data, facilitating the processing of complex distributions and outliers [6]. During the decision-making process, the trust relationships and similarities in opinions among decision-makers are used to construct a relationship network among decision-makers, and the Louvain algorithm is adopted for the clustering analysis. The research gap between this paper and previous studies lies in the use of a mixed distance calculation formula for calculating the similarity of expert opinions, which improves the accuracy of the weight calculations.

Therefore, reducing the dimensionality of large-scale groups and objectively obtaining weight data to simplify the problem-solving process are important.

Determining weights is a key step to ensuring the accuracy and effectiveness of the LSGDM results [7]. By assigning different weights to different decision-makers or attributes, their importance or influence in the decision-making process can be more accurately reflected. Researchers have developed various methods to quantify and allocate weights to indicate the importance of different decision-makers' opinions or decision criteria. The calculation idea of expert weights originates from the weighted sum of the squared Euclidean distance and the squared Wasserstein distance to improve the accuracy and operability of the weight determination process.

The ultimate goal of LSGDM is to reach a group-satisfactory consensus, forming a final ranking of the options [8]. In fact, with the increase in the number of decision-makers, the number of adjustment rounds also increases, and the complexity of obtaining consensus opinions from a large-scale group simultaneously increases significantly. Therefore, this paper uses a two-stage consensus measurement and feedback mechanism to accelerate the CRP. In the first stage, the outliers are removed through mean and variance in the clustered decision groups, and the decision representatives in the decision groups are finally selected to reduce the decision scale. Secondly, to prevent the situation where there is more than one outlier in the decision-making process, a dual minimum consensus level is set. When the adjustments to the first minimum consensus level reach a certain number without reaching a consensus, it is considered that there is more than one decision-maker with a large decision difference from the others. The scores of decision-makers are adjusted for the second minimum consensus level. After obtaining the final scores, the prospect–regret theory is integrated to more comprehensively understand the impact of the decision-makers' bounded rationality on the decision results [4]. These two theories mitigate the influence of psychological factors before and after the decision-making process, effectively integrating the decision-makers' bounded rationality into the outcomes to produce the final decision result.

In an uncertain environment, rational decisions based on the expected utility cannot efficiently explain certain actual decision behaviors [9]. Therefore, within the framework of behavioral decisions, research on the cognitive limitations of decision-makers, the subjective psychological factors of decision-makers, and the psychological impact of the environment on decision-makers is becoming increasingly important. As scholars delved deeper, Kahneman [10] proposed the prospect theory, and Bell, Loomes, and Sugden [11] proposed the regret theory, providing new ideas for addressing uncertain decision problems considering decision-makers' psychological behaviors. This paper combines the prospect–regret theory [4] with the final results of the CRP to obtain the final ranking of the options. The prospect theory explains how decision-makers have varying attitudes towards gains and losses, highlighting the influence of emotions, but it does not directly address the regret that might occur after making decisions. The regret theory, on the other hand, emphasizes the future regret emotions without fully considering the balance between potential gains and losses, often resulting in more conservative decisions. By integrating these two approaches, the prospect–regret theory can address their individual limitations, resulting in decision outcomes that better align with people's behaviors in diverse situations. In summary, how to minimize the influence of outlier decision-makers after clustering to achieve satisfactory results for the group and effectively prevent situations where consensus requirements are not met even after multiple iterations.

In conclusion, in existing LSGDM methods, many studies on consensus-reaching mechanisms exist, but few use two-stage processing with secondary fine-tuning solutions. Owing to the large scale of LSGDM, experts have diverse backgrounds and cognitive differences, making it difficult to achieve a high consensus among experts on one decision-making process [12,13]. As the number of decision-makers increases, the number of adjustment rounds also increases, and the complexity of obtaining large-scale group consensus opinions significantly rises. Therefore, it is necessary to design a reasonable consensus feedback mechanism to improve group consensus levels and ensure the reliability of decision results.

The structure of this paper is as follows: the second section reviews the literature on LSGDM and the sentiment analysis. The third section provides an overview of the foundational knowledge framework for LSGDM methods and the prospect–regret theory. The fourth section introduces the improved Louvain algorithm for clustering and the CRP based on dual fine-tuning. The fifth section illustrates and tests our proposed LSGDM model through a case study of purchasing solar garden lights online and examines the strengths and weaknesses of our approach through both quantitative and qualitative comparative analyses, as well as a sensitivity analysis. The sixth section concludes the paper and offers suggestions for future research.

2. Related Work

In this section, we will break down the content into three distinct parts. Firstly, Section 2.1 offers a comprehensive literature review on the sentiment analysis. Following this, Section 2.2 delves into the existing research on the clustering analysis. Finally, Section 2.3 provides an in-depth literature review on the CRP.

2.1. Sentiment Analysis

The sentiment analysis plays a crucial role in LSGDM, especially when handling the vast amount of review data from social media, online forums, and e-commerce websites. Through the sentiment analysis, sentiment can be effectively introduced and quantified. These sentiment data help decision-makers or consumers understand the attitudes and tendencies toward a particular product or issue. Zhang et al. [14] established a multi-granularity probabilistic linguistic information system using probabilistic linguistic term sets. This method quantitatively analyzes users' emotional expressions through the sentiment analysis. Liang et al. [15] proposed an integrated decision support model that collects linguistic information from each review through the sentiment analysis and converts it into a linguistic intuitionistic standard cloud of the product, thus ranking hotels.

These models analyze the emotional tendencies within comments to help decision-makers understand user satisfaction and focal points. Compared with traditional small-scale datasets, online data collection can provide larger and richer samples, enhancing the accuracy and reliability of decisions. Additionally, online data collection can be updated in real-time, ensuring that the decision basis is always up-to-date. By analyzing the sentiment in online review data, decision-makers can better grasp user psychology, and optimize product design and marketing strategies, thereby gaining an advantage in the competitive market. In summary, sentiment analysis methods help to accurately examine online review data and provide reliability in interpreting the emotional classification of data.

2.2. Clustering Analysis

Conventional clustering approaches rely on the similarity of viewpoints among decision-makers, such as K-means clustering algorithms [16], hierarchical clustering algorithms [17], and vector space-based clustering algorithms [18].

Vincent et al. [19] pointed out that the Louvain algorithm, as an efficient community discovery algorithm, is particularly suitable for large-scale networks. Wu et al. [20] proposed an LSGDM model based on the Louvain algorithm using interval type-2 fuzzy sets, determining the weights of decision-makers and community submodules based on community network characteristics. It is noteworthy that most of the existing research on LSGDM problems based on social network relationships focuses on the clustering of LSGDM, with less improvement in the calculation process of expert similarity before the clustering analysis. This paper uses a mixed-distance method combining Euclidean distances with Wasserstein distances to calculate the opinion similarity between decision-makers.

Xu et al. [21] determined the weights of the subgroups based on the consistency degrees of the subgroup preference relationships. Wu et al. [20] divided a network into several communities and then obtained the centrality of the entire network and the communities by averaging the fused centrality of all the members, obtaining the community's weight based on the inverse relative distances between the community centrality and the overall network centrality. However, some methods of solving index weights have limitations and cannot cope with complex decision environments. Unlike the above literature, this paper also calculates the weight of each expert. This paper also calculates the weight of each expert to improve the accuracy and operability of the weight determination process.

2.3. CRP and Decision Result Generation

The CRP can effectively reduce the contradictions between decision-makers, facilitating the production of decision outcomes. The key to enhancing consensus lies in how to set the adjustment range for scores during the CRP to achieve a better decision consensus. Many scholars have offered various solutions. For example, Xu et al. [21] established a two-stage consensus method, where the two phases refer to the consensus within the group decision representatives and the consensus between groups. In addressing outliers within groups by modifying their evaluation values, the approach involves directly replacing the outliers' values with the desired ones. Tang et al. [22] constructed a subgroup adaptive CRP composed of mixed strategies. This model proposes different feedback mechanisms for varying degrees of subgroup inter-consensus and intra-consensus, which can be realized by increasing or decreasing the fixed values of outliers when modifying evaluation values. However, the aforementioned studies have considered adjustments to decision scores but lack flexibility, so are unable to make reasonable adjustments based on actual scores. In this paper, the size of the adjustment range is determined by the amount of scoring, effectively preventing a decrease in the consensus due to an excessive adjustment of scores. As the number of group decision-makers increases, the number of adjustment rounds also increases, significantly raising the complexity of obtaining large-scale group consensus opinions. Therefore, a two-stage consensus measurement and feedback mechanism can help to accelerate the consensus-reaching process.

The selection of adjustment subjects during the decision-making process also plays a crucial role in the decision outcome. Palomares et al. [23] designed an LSGDM model based on the FCM clustering algorithm, achieving effective dimensionality reduction by grouping large-scale decision-makers. Liu et al. [24] proposed a partial binary tree DEA-DA cyclical classification model to categorize decision-makers. However, existing methods may not pay attention to the adjustment of the decision scores themselves, and there may be situations where the adjustments are too large or too small. Palomares et al. [23] and Liu et al. [24] failed to fully consider the situation where an excessive number of decision adjustment rounds fails to reach a consensus level. These studies have not focused on situations where multiple cycles still fail to meet the consensus requirements during the decision-adjustment process. Zhang et al. [25] proposed a consensus model for MAGDM using multi-granular HFLTSs, optimizing preference adjustments. Li et al. [26] also proposed consensus models for ordinal classification-based GDM problems with heterogeneous preferences. Yuan et al. [27] optimized IFPRs for robust consensus in large-scale GDM problems. In fact, as the number of decision-makers increases, the complexity of obtaining consensus opinions from a large-scale group also significantly increases. To address this, this paper sets a dual minimum consensus level, reducing the time and adjustment costs required to reach a consensus level by increasing the number of adjusters.

Zhang et al. [28] explored a group consensus model method in the context of interval type-2 fuzzy sets. To alleviate the complexity of reaching a consensus among decision-makers, this model introduces random variables to complete the step of selecting consensus-level thresholds. Palomares et al. [23] designed an LSGDM model based on the FCM clustering algorithm, grouping group decision-makers to achieve effective dimensionality reduction. Liu et al. [24] proposed a partial binary tree DEA-DA cycle classification model to classify decision-makers. However, the above studies do not focus on the situation where multiple cycles still fail to meet the consensus requirements during the CRP of LSGDM.

The generation of the final decision is a key step in the CRP, and this paper incorporates the behavioral decision theory at this step. Within the behavioral decision theory, the prospect theory [29] mainly focuses on the decision makers' degree of delight in making decisions. Meanwhile, the regret theory has also yielded many excellent research results in LSGDM. For instance, Jin et al. [30] proposed a linguistic distribution LSGDM technique that applies statistical inference principles and incorporates the regret theory to address the regret-averse psychological characteristics among decision makers. However, relatively speaking, they have not considered the comprehensive impact of both information and regret on decision-making. The integration of these two aspects has also been explored by many scholars. For example, Wang et al. [31] studied a three-way decision model using the regret theory within a hesitant fuzzy environment. Furthermore, they introduced a novel regret–rejoice function in their research. Tian et al. [32] described a CRP for multi-criteria ranking issues with multiple experts based on probabilistic linguistic term sets, which takes into account the decision makers' regret–rejoice emotions during the decision-making process. Jin et al. [33] constructed a regret–rejoice PLMDEA model based on the regret theory, which considered the regretful attitudes of decision-makers. We incorporate the regret–elation theory into the process of ultimately reaching a decision, allowing the decision outcome to not only take into account the overall collective opinion but also to integrate the behavioral decision theory, facilitating the generation of decision results that are more aligned with objective reality.

3. Materials and Methods

This section will briefly introduce the sentiment analysis, the Louvain algorithm, the CRP, and the prospect–regret theory.

3.1. Text Preprocessing Techniques

The sentiment analysis is a technique that analyzes text data after segmentation to identify and understand the emotions and sentiments expressed therein [34,35]. This section will introduce the key steps required for the sentiment analysis.

3.1.1. Chinese Word Segmentation

This article uses ChatGPT 4.0 (Conversational Generative Pre-trained Transformer) for Chinese word segmentation. Compared with traditional segmentation methods, ChatGPT has a higher adaptability, and its deep learning-based model can effectively understand context and handle polysemy [36].

3.1.2. Creating an Emotion Dictionary

User evaluations often incorporate emotional language, utilizing adjectives, adverbs, and negations to convey their opinions and sentiments about products. Adjectives reflect attitudes toward items, while adverbs and negations indicate the extent of favorability or unfavorability. The sentiment analysis entails extracting these linguistic cues from user feedback and transforming them into valuable insights for assessing products across various dimensions. This article will employ the sentiment analysis utilizing emotion dictionaries to statistically gather collections of positive, neutral, and negative sentiment terms.

3.1.3. Translate the Quantitative Calculation of Emotions

LTP, a natural language processing tool developed in China, automates a range of tasks, including part-of-speech tagging and semantic role labeling [37]. By using LTP to conduct a dependency syntax analysis on product reviews, the identified sentiment words are categorized into three levels: negative (−1), neutral (0), and positive (1). The formula for sentiment quantification is as follows:

$$Score_{ij}^{q} = p(O_{ij}^{q}) \times deg(O_{ij}^{q}) \times \left[(-1)_{ij}^{q}\right]^{N}, \tag{1}$$

where O_{ij}^{q} denotes the sentiment word about attribute C_j of the product in the online review e_i^q, and $p(O_{ij}^{q})$ denotes the polarity of the sentiment word O_{ij}^{q}. $deg(O_{ij}^{q})$ represents the sentiment intensity of the sentiment word O_{ij}^{q} influenced by the degree adverb.

3.2. The Louvain Algorithm

The Louvain algorithm, as a method based on modularity optimization, is widely used in the discovery of community structures in complex networks [38]. Its core idea is to maximize the modularity of the network by iteratively optimizing the community assignment of the nodes. Through this locally optimized strategy, the Louvain algorithm can effectively discover community structures in networks and has a high computational efficiency, making it suitable for handling large-scale networks. In this study, a social relationship network is established based on the similarity of opinions among experts and trust relationships. The Louvain algorithm is then used to cluster large populations.

3.2.1. Modularity

In the Louvain algorithm, modularity is used as a metric to evaluate the quality of the network's community structure. The concept of modularity quantifies the difference between the density of connections within the modules and the expected density of random connections. Modularity serves as the objective function, and the algorithm discovers community structures by continuously optimizing this metric [39].

The definition of modularity is as follows:

$$Q = \frac{1}{2m}\sum_{i,j}\left(A_{ij} - \frac{k_i k_j}{2m}\right)\delta(C_i, C_j), \tag{2}$$

where A_{ij} represents the number of edges connecting the node i and the node j in the network, k_i and k_j represent the degrees of nodes i and j, respectively, m represents the total number of edges in the network, C_i and C_j represent the community labels of nodes i and j, respectively, and $\delta(C_i, C_j)$ is an indicator function that equals 1 when $C_i = C_j$ is true, and 0 otherwise.

3.2.2. The Euclidean Distance

The Euclidean distance considers the differences of the data points in each dimension, which has the characteristics of intuitiveness and ease of understanding. In the Louvain algorithm, using Euclidean distances helps to measure the similarity between nodes, thereby promoting community partitioning and clustering results. The Euclidean distance is applied in the calculation of node similarity [40] using the formula:

$$d_{ij} = \sqrt{\sum_k \left({A_{ij}}^2 - {A_{jk}}^2\right)}, \tag{3}$$

where d_{ij} represents the Euclidean distance between the node i and the node j, and A_{ik} and A_{jk}, respectively, represent the connection weights of nodes i and j in the adjacency matrix A.

3.2.3. The Process of the Louvain Algorithm

This section will introduce the process of using the Louvain algorithm, which consists of the following steps:

Step 1: Construct the social network. Let the set of nodes in the network be N, where each node i represents an individual or entity. The relationships between the nodes are represented by edges. Let the set of edges in the network be E, where each edge (i, j) represents some form of association between the node i and the node j. The relationships between the nodes and edges are represented using a graph structure $G = (N, E)$, typically implemented using an adjacency matrix or adjacency list. In the initialization phase, each node is initially considered as a separate community: $C_i = i, \forall i \in N$.

Step 2: Iterative optimization. Iterate over each node i and calculate the modularity gain when the node joins its neighboring community:

$$\Delta Q_{i \to j} = \frac{\sum_{in} + \frac{\sum_{tot} k_{i,in}}{2m}}{2m} - \left(\frac{\sum_{tot} k_{in}}{2m} \right)^2, \quad (4)$$

where $\sum_{in}$ represents the sum of weights of the edges from the node i to the interior of the community n, $\sum_{tot} k_{i,in}$ represents the sum of weights of the edges from the node i to all edges in community n, and m represents the total weight of all the edges in the network.

Step 3: If moving a node to a neighboring community yields the maximum modularity gain, execute the node movement operation. Merge the nodes with the same community label into a supernode.

Step 4: Repeat Steps 2 and 3 on the new network until further optimization of modularity is not possible. The final communities are the node groupings at the end of the iteration.

3.3. CRP

The ultimate goal of the LSGDM is to achieve a result satisfactory to the group, establish a consensus, and further obtain the group's decision. To this end, this paper divides the CRP into two stages [41,42].

Before adjusting the CRP, each decision-maker needs to express their preferences and provide subjective opinions on the decision-making matter.

During the initial stage, a consensus is attained within the decision groups by refining opinions to obtain the collective viewpoint of each group. Decision-makers' perspectives within each group are then combined to ascertain the group's preference and calculate the overall consensus. If the consensus does not meet the required standard, feedback mechanisms are used to adjust individual opinions. If a consensus is achieved through consensus measurement, the process moves to the second stage.

In the second stage, adjustments to opinion preferences continue based on the preferences provided by different groups in the first stage. If the ultimate consensus threshold is not achieved, group feedback is iteratively provided to refine the decision preferences within the groups, with the aim of enhancing the consensus levels within the group. If the required level of consensus is achieved, this preference is considered the final decision result.

The flowchart of the CRP is shown in Figure 1.

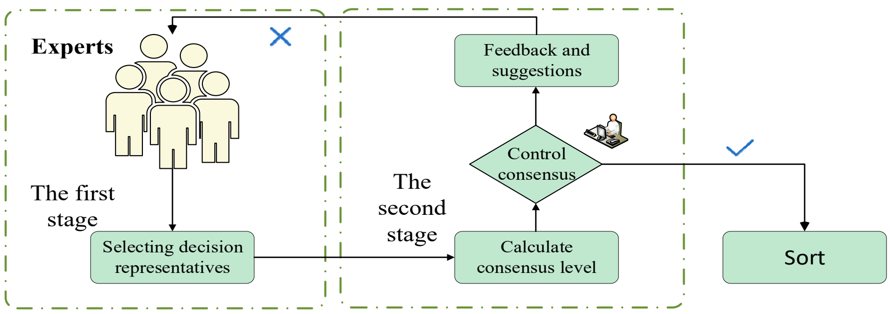

Figure 1. The Overall Plan for the CRP.

3.4. Prospect–Regret Theory

Using the prospect–regret theory, it is found that people evaluate decisions based on reference points, which can be the current state or expected benchmarks. People compare the differences between decision outcomes and reference points to assess the value of the decision and the likelihood of regret. The following are the core steps of using the prospect–regret theory:

Step 1: Use Formula (5) to calculate the value function for each decision-maker, which involves the difference between each decision-maker's score and the average score of all the decision-makers, serving as their losses and gains.

$$v(\Delta x_{ij}) = \begin{cases} (\Delta x_{ij})^{\alpha} & \Delta x_{ij} \geq 0 \\ -\lambda(-\Delta x_{ij})^{\beta} & \Delta x_{ij} < 0' \end{cases} \tag{5}$$

where λ represents the loss aversion coefficient, with a larger value indicating that the decision-maker is more sensitive to losses.

Step 2: Obtain the prospect value matrix V_{ij} according to Formula (6), where w represents the attribute weights. Additionally, the maximum prospect value V_i^+ and the minimum prospect value V_i^- can be obtained.

$$V_{ij} = v(\Delta x_{ij})w. \tag{6}$$

Step 3: Obtain the delight value matrix R_{ij} according to Formula (7) and the Hamming distances.

$$Z_i(x) = \sum_{j}^{m} (R_{ij}(x) + G_{ij}(x)). \tag{7}$$

Step 4: Obtain the regret value matrix G according to Formula (8) and the Hamming distances.

$$G_{ij}(x) = 1 - \exp\left[-\delta\left|\frac{V_{ij}(x) - V_{ij}^{-}(x)}{V_{ij}^{+}(x) - V_{ij}^{-}(x)}\right|\right]. \tag{8}$$

Step 5: Calculate the delight–regret value using Formula (9).

$$Z_i(x) = \sum_{j}^{m} (R_{ij}(x) + G_{ij}(x)). \tag{9}$$

4. The LSGDM Method Based on Dual Fine-Tuning

The first step of this study involves a sentiment analysis based on online review data. Secondly, a social relationship network is constructed by integrating expert opinions' similarity and trust relationships. Based on this, an LSGDM with dual fine-tuning is adopted. Finally, ranking is conducted using the prospect–regret theory.

4.1. Data Processing and Sentiment Analysis

Since consumers are heavily influenced by online product reviews during the consumption process, the primary step is to effectively extract and analyze the sentiment factors from the review data and then accurately and effectively convert them into preference datasets. This section will extract five different brands of solar lighting products from online platforms as the solution set to verify the feasibility of the sentiment analysis methods. The extracted data include not only online reviews but also the star ratings given by consumers for the products.

4.1.1. Data Processing

Since the raw online review data may contain a large amount of noise, data processing can help to filter out irrelevant information and improve data quality, making it suitable for sentiment analysis models to enhance accuracy and efficiency. The following are the three steps of data processing:

(1) Text cleaning: Since the collected data may have some noise, this section first removes duplicate reviews and some emoticons to create a new text.

(2) Data tokenization: This section uses ChatGPT tokenization for extracting keywords and the sentiment analysis in the subsequent steps.
(3) Stopword filtering: The tokenized text may contain words like particles, numbers, mathematical symbols, English characters, etc., which do not affect the results. This paper filters out these stop words to avoid affecting the effectiveness of the sentiment analysis.

4.1.2. Constructing the Sentiment Dictionary

After the tokenization process described in Section 3.1.1, each sentence from the reviews is divided into individual words. The sentiment analysis primarily determines the sentiment expressed by the entire sentence based on the sentiment orientation of the words. This section assists the subsequent steps by constructing dictionaries of positive and negative sentiments. The positive emotion lexicon and negative emotion lexicon are shown in Tables 1 and 2, respectively.

Table 1. Building a positive emotion lexicon.

Broad range, affordable, convenient, satisfactory, likable, elegant, user-friendly, pleasant, patient, good review, value for money, thoughtful, worthy, reliable, beautiful, high brightness, long lifespan, attractive, repurchase, warm, highly recommended, cost-effectiveness, recommend, soft, good.

Table 2. Building a negative emotion lexicon.

Very dark, unpleasant, troublesome, missing parts, not bright, bad review, not in accordance, really bad, disappointed, useless, plastic packaging, deceptive, misleading, inferior, abnormal sound, not up to standard, mediocre, too dim, deceptive, cracked, glaring, return, very small, collapsed, deformed, damaged.

4.1.3. Sentiment Orientation Ratio

This section conducts a sentiment evaluation based on the star ratings collected from consumers for various brands. Ratings of 1 and 2 stars are classified as negative, 3 stars as neutral, and 4 and 5 stars as positive. The percentage of emotional tendency is shown in Table 3.

Table 3. The percentage of emotional tendency for five brands.

	Negative	Neutral	Positive
Xiang Zhe	27.3%	27.3%	45.4%
Shu FuJia	36.4%	36.4%	27.2%
Shuo Shi	18.2%	54.5%	27.3%
BELAN	30.0%	30.0%	40.0%
You Chi	10.0%	20.0%	70.0%

4.1.4. The Fuzzy Number Acquisition

Mapping the adverbs describing the degree of good or bad for a certain attribute of the product in the reviews to trapezoidal fuzzy numbers. The correspondence table between product ratings and trapezoidal fuzzy numbers is shown in Table 4.

Table 4. The correspondence table between product ratings and trapezoidal fuzzy numbers.

Product Ratings	Trapezoidal Fuzzy Numbers
Very Poor	(0.0, 0.0, 0.1, 0.2)
Poor	(0.1, 0.2, 0.2, 0.3)
Fairly Poor	(0.2, 0.3, 0.4, 0.5)
Moderate	(0.4, 0.5, 0.5, 0.6)
Fairly Good	(0.5, 0.6, 0.7, 0.8)
Good	(0.7, 0.8, 0.8, 0.9)
Very Good	(0.8, 0.9, 1.0, 1.0)

Human language is used to describe the advantages and disadvantages of product attributes. To convert them into fuzzy numbers, the following fuzzy number conversion process is conducted:

Symbols used in the conversion process: let us denote the score, ranging from $[-3, 3]$. Trapezoidal fuzzy numbers are denoted as (a, b, c, d), triangular fuzzy numbers as (e, f, g), and fuzzy numbers as f. The specific steps for converting the product evaluations into fuzzy numbers are as follows:

Step 1: Assign scores to different brands and attributes based on adverbs of degree to ensure that the scores fall within the range of trapezoidal fuzzy numbers, calculated as $S = \frac{s}{3}$.

Step 2: Use Formula (10) to calculate the left triangular fuzzy number fl and the right triangular fuzzy number fr (replaced by f_1 in the following formulas). When calculating the value corresponding to the left triangular fuzzy number, input (a, b, c), and when calculating the value corresponding to the right triangular fuzzy number, pass in (b, c, d):

$$\begin{gathered} \text{If } S \leq e,\ f_1 = 0; \\ \text{If } e \leq S \leq f,\ f_1 = \tfrac{S-e}{f_1-e}; \\ \text{If } f \leq S \leq g,\ f_1 = \tfrac{g-S}{g-f_1}; \\ \text{If } g \leq S,\ f_1 = 0. \end{gathered} \tag{10}$$

Step 3: Utilize the following Formula (11) to determine the fuzzy number:

$$f = \frac{fl + fr}{2}. \tag{11}$$

4.2. The Improved Louvain Algorithm

Construct a relationship network among experts based on trust relationships and the similarity of opinions among decision-makers, and then utilize the improved Louvain algorithm on this network to cluster large populations and obtain aggregated weights.

4.2.1. The Problem Description

The formal representation of fuzzy large-group decision-making with dual fine-tuning in this paper is as follows:

Let $X = \{x_1, x_2, \ldots, x_m\}(m \geq 2)$ be the set of alternative solutions, where x_i represents the *i-th* solution; $C = \{c_1, c_2, \ldots, c_n\}(n \geq 2)$ be the set of attributes, where c_j represents the *j-th* attribute.

Similarly, let $E = \{e_1, e_2, \ldots, e_k\}(k \geq 20)$ be the set of decision-makers, where e_f denotes the f-*th* decision-makers; $\omega = \{\omega_1, \omega_2, \ldots, \omega_k\}^T$ be the weight vector of the decision-makers, where ω_f denotes the weight of the f-*th* decision-makers, satisfying $\omega_f \geq 0$ and $\sum_{f=1}^{k} \omega_f = 1$.

This paper assumes that each decision-maker's score matrix during the CRP is denoted as w. The average score matrix is represented by avg_g, the variance matrix by var_g, the consensus matrix by con, and the group consensus by g_con. Additionally, the distances matrix between each pair of decision representatives is denoted by dis.

In the prospect–regret theory, it is assumed that the value function matrix is V, the prospect value matrix is *pre*, the joy value matrix is P, the regret value matrix is Q, and the joy–regret matrix is *Re*.

4.2.2. The Wasserstein Distance

The Wasserstein distance, alternatively referred to as the Earth Mover's distance, originates from transportation problems. In transportation problems, resources need to be transported from one location to another, but the distances and transfer costs between each pair of locations may vary. The calculation process of Wasserstein distances can be viewed as the optimal transportation of one probability distribution to another, where the cost of each transfer is associated with the difference between the probability distributions. Specifically, given two probability distributions, μ and ν, the Wasserstein distance is defined as the minimum total cost of transporting one probability distribution to another. This cost can be computed by finding the best matching between the two distributions, where the cost of transferring each element from one distribution to another is proportional to the distances between them. The calculation of Wasserstein distances can be achieved using linear programming or convex optimization-based methods [43].

Given two probability distributions, μ and ν, their Wasserstein distance is defined as:

$$W_p(\mu, v) = \left(\inf_{\gamma \in \Gamma(\mu, v)} \int_{R^d \times R^d} \|x - y\|^p d\gamma(x, y)\right)^{1/p}, \tag{12}$$

where p is the order of the norm (usually 1 or 2), $\Gamma(\mu, v)$ is the set of all the joint distributions with marginal distributions μ and v, and $\gamma(x, y)$ represents the joint distribution where x and y are from the two probability distributions, respectively.

4.2.3. The Methodology of the Louvain Algorithm

Based on the list of fuzzy number matrices, the similarity of opinions among decision-makers is determined using a combination of the Euclidean distances formula and the Wasserstein distances formula. The distances formula is as follows:

$$d_{ij}^m = \alpha d_{ij}^e + (1 - \alpha) d_{ij}^w, \tag{13}$$

where α is a weight coefficient used to balance the importance of the Euclidean distances and the Wasserstein distances. Additionally, α is generally set to the average value to ensure equal relative contributions of both distances in the distance measurement.

The similarity matrix R is obtained according to Formula (14):

$$r_{ij} = 1 - \frac{1}{m} \sum_{i=1}^{m} \sum_{j=1}^{n} d_{ij}^m. \tag{14}$$

By integrating the trust relationships among decision-makers with the similarity of opinions, we derive the relationship coefficients between decision-makers using Formula (15), yielding the relationship matrix among decision-makers:

$$y_{ij} = \frac{1}{2} p_{ij} + \frac{1}{2} r_{ij}. \tag{15}$$

When calculating the weights of the clusters and decision-makers, the aggregate scale and the degree centrality of the network are considered. The weights of each cluster $U = \{u_1, u_2, u_3, \ldots, u_q\}$ are obtained using Formula (16), followed by the calculation of the weights of each decision-maker $\omega = \{\omega_1, \omega_2, \omega_3, \ldots, \omega_k\}$ based on Formula (17):

$$u_q = \frac{\sum\limits_{i \in u_q} y_{ij}}{2 \sum y_{ij}} + \frac{N_q}{2k}; \tag{16}$$

$$\omega_k = \frac{\sum\limits_{j \in u_q} y_{kj}}{\sum\limits_{i \in u_q} \sum\limits_{j \in u_q} y_{ij}}. \tag{17}$$

Finally, the specific algorithm steps are presented in Algorithm A1 of the Appendix A.

4.3. The CRP Based on Dual Fine-Tuning

This section will introduce the two stages of the CRP based on dual fine-tuning in detail. The specific steps will be provided in Algorithm A2 of the Appendix A.

In the actual decision scoring process, decision-makers' scores for each product are often influenced by significant personal subjective emotions. To address this issue, a two-stage group CRP is established to obtain objective product ratings.

The CRP adopts two stages to effectively reduce the decision-making and adjustment process, improve decision-making efficiency, and reduce time complexity.

In the first stage, decision scores within different decision groups are derived:

After clustering using the improved Louvain algorithm, the matrix $w[i][j][k]$ is obtained. Then, the average score matrix $avg\_g[j][k]$ is calculated by averaging each row of matrix w. Next, the variance var_g is calculated using Formula (18) to indicate the dispersion of each score relative to the average value.

$$\left(\frac{1}{x}\sum_{j=0}^{x-1}\left(\frac{1}{y}\sum_{k=0}^{y-1}(w[i][j][k]-avg\_g[j][k])^2\right)\right). \tag{18}$$

In the second stage, adjustments are made for the dual minimal consensus. It is important to note that although the letter selection for the number of representatives remains unchanged in the second round, it now represents the decision representatives selected in the first round:

First, use Formula (19) to calculate the distance matrix $dis[n][n]$ between any two decision-makers, finding the Euclidean distance between them, where a and b are the identifiers of any two selected decision representatives:

$$\left(\frac{1}{x}\sum_{j=0}^{x-1}\left(\frac{1}{y}\sum_{k=0}^{y-1}(w[i][j][k]-avg\_g[j][k])^2\right)\right). \tag{19}$$

Next, calculate the consensus degree between a decision-maker and all other decision-makers using the distance matrix $dis[n][n]$ and Formula (20). Obtain an n-dimensional matrix $con[n]$:

$$1-\frac{1}{n}\sum_{j=0}^{n-1}\frac{dis[i][j]}{18}. \tag{20}$$

Then, use Formula (21) to calculate the average consensus degree matrix to obtain the final group consensus degree g_con:

$$\frac{1}{n}\sum_{i=0}^{n-1}con[i]. \tag{21}$$

Finally, Formula (22) is used for the score adjustment:

$$\begin{gathered}\text{If } w[i][j][k] > avg\_p[j][k],\\ \text{then } w[i][j][k]-=\tfrac{avg\_p[j][k]}{9};\\ \text{If } w[i][j][k] < avg\_p[j][k],\\ \text{then } w[i][j][k]+=\tfrac{avg\_p[j][k]}{9}.\end{gathered} \tag{22}$$

The flowchart of the dual fine-tuning CRP is shown in Figure 2.

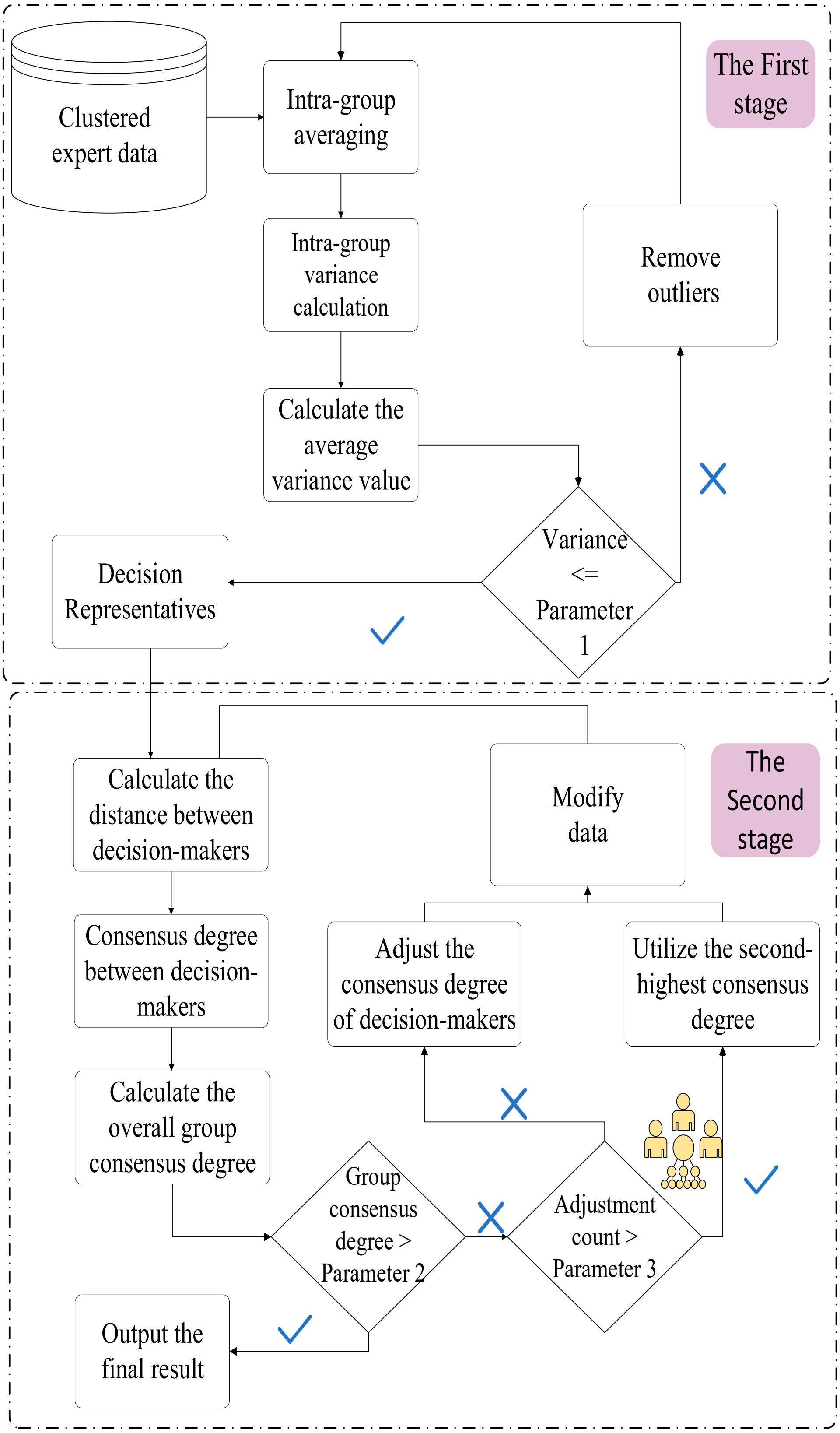

Figure 2. The CRP with dual fine-tuning.

4.4. Prospect–Regret Theory

The prospect–regret theory can effectively prevent the regret or elation that decision-makers might experience after the decision results are generated. In this section, we will combine the existing knowledge of the prospect–regret theory with the final results of the CRP to obtain the ranking of the options. This method can effectively address the impact of decision-makers' regret or elation on the experimental results. The specific experimental steps are detailed in Algorithm A3 of the Appendix A.

5. Instance Analysis

This section will verify the decision-making model based on dual minimum value fine-tuning using the case of solar light selection, and present the steps of the specific algorithm. The overall experimental process is shown in Figure 3. The overall experimental steps are seen in Algorithm A4 of the Appendix A. In addition, this section not only compares the classical multi-attribute decision-making methods with the method presented in this paper, but it also conducts a sensitivity analysis on the method presented in this paper using different parameter values.

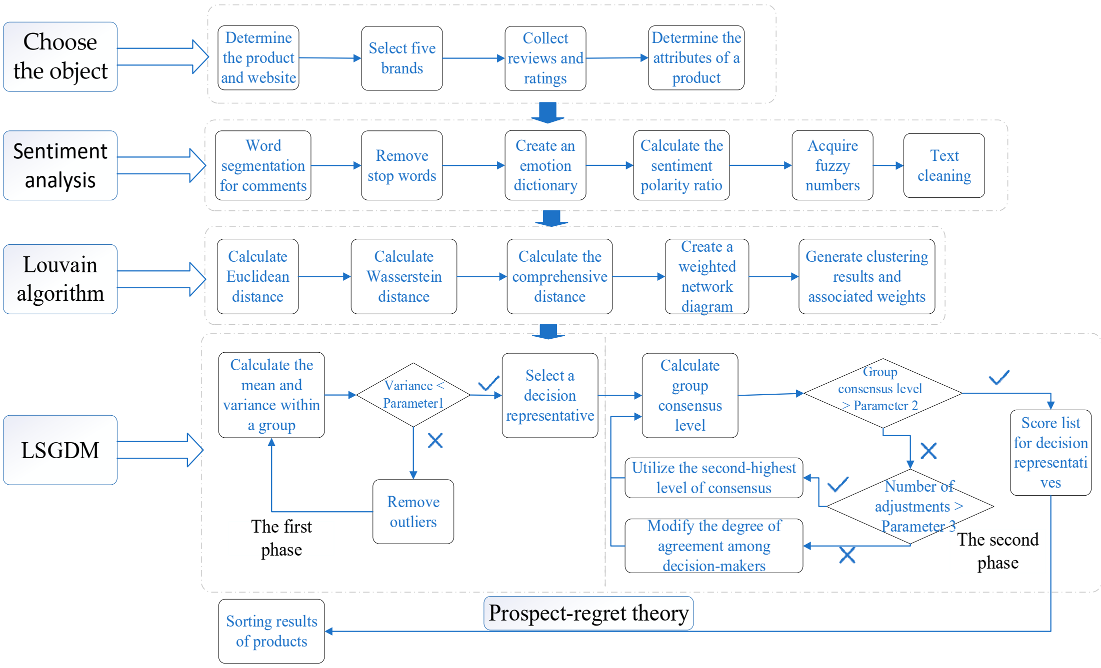

Figure 3. The experimental procedure flowchart.

5.1. Instance Description

The data used in this section come from reviews of solar streetlights sold on an online platform. To ensure the data are broadly representative, this article selects five solar light brands with a high sales volume and rich reviews, including Xiangzhe, Shufujia, Shuoshi, BELAN, and Youchi.

First, assume $X = \{x_1, x_2, x_3, x_4, x_5\}$ to be the set of alternative solutions, which are "Xiang Zhe", "Shu Fu Jia", "Shuo Shi", "BELAN", and "You Chi".$C = \{c_1, c_2, c_3, c_4, c_5, c_6\}$. The meanings they represent are brightness, duration of light, price, appearance, service attitude, and product quality. Let $E = \{e_1, e_2, e_3, e_4, \ldots, e_{30}\}$ represent the decision-makers among them. Use $V = \{v_1, v_2, \ldots, v_n\}$ to represent the different groups after clustering the decision-makers.

Apply this dataset to the decision-making model proposed in Section 3 for decision-making, with the following steps:

Step 1: Process the crawled review data according to the first part of Section 3, obtaining a score matrix for different decision-makers for different brands. Use the formula to derive a fuzzy number matrix from the score matrix.

Step 2: Cluster all the obtained fuzzy number matrices as described in the second part of Section 3, deriving inter-group weights, intra-group weights, and clustering group results, as shown in Table 5. The results of clustering all the obtained fuzzy number matrices are shown in Figure 4.

Table 5. Clustering and decision-maker weight results.

Clustering Result	Expert Individuals and Weights	Cluster Weighting
e_1	$v_4(0.08), v_{10}(0.07),$ $v_0(0.08), v_{16}(0.08),$ $v_{20}(0.08), v_{21}(0.06),$ $v_{23}(0.08), v_{28}(0.08),$ $v_{15}(0.06), v_{12}(0.06),$ $v_{17}(0.08), v_{22}(0.06),$ $v_{30}(0.07),$	0.41
e_2	$v_1(0.08), v_{14}(0.09),$ $v_8(0.08), v_{11}(0.09),$ $v_5(0.08), v_{18}(0.08),$ $v_6(0.09), v_{27}(0.08),$ $v_{26}(0.08), v_{13}(0.08),$ $v_{19}(0.09), v_{29}(0.08)$	0.39

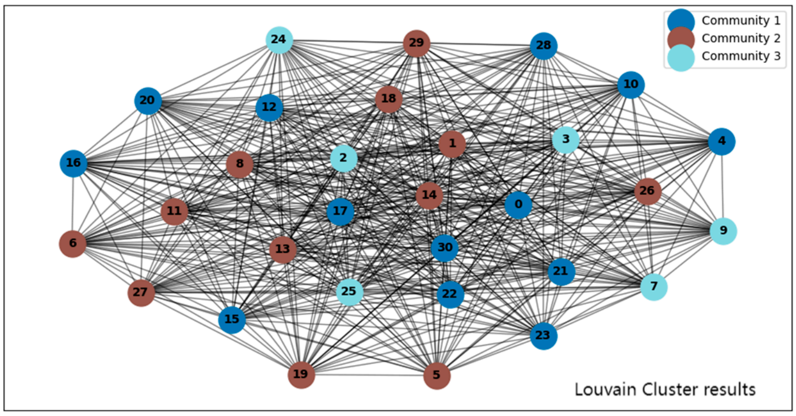

Figure 4. The clustering result graph.

Step 3: Based on the clustering groups and weights obtained in Step 2, conduct the first round of the consensus adjustment. In this round, the scores, means, and variances will be calculated to remove the outliers within each group. Finally, the decision-maker score matrix for each group is selected as follows:

$$\begin{bmatrix} 2.45 & 2.20 & 0.30 & 0.20 & 0.10 & 1.70 \\ 2.05 & -0.20 & 0.50 & 1.40 & 0.20 & 2.20 \\ 2.05 & 2.05 & 0.15 & 0.85 & 0.05 & 2.60 \\ 2.00 & 1.25 & 0.10 & 2.00 & 0.10 & 2.70 \\ 2.05 & 0.89 & 0.00 & 0.50 & 0.15 & 0.55 \end{bmatrix},$$

$$\begin{bmatrix} 0.50 & 1.80 & 0.00 & 2.30 & 0.10 & 1.60 \\ 2.40 & 0.80 & 0.20 & -0.30 & 0.00 & 0.10 \\ -0.20 & 0.50 & 2.60 & 1.60 & 0.10 & 2.30 \\ 0.20 & 2.10 & 0.00 & 0.40 & 0.10 & 1.60 \\ 0.20 & 0.40 & 0.00 & 1.50 & 0.10 & 0.30 \end{bmatrix},$$

$$\begin{bmatrix} 2.20 & 1.50 & 0.00 & 1.40 & 1.90 & 0.10 \\ 1.50 & 2.40 & 0.10 & 1.10 & 0.00 & 1.30 \\ 2.50 & 2.30 & 0.00 & 0.30 & 0.10 & 1.60 \\ 2.40 & 2.80 & 0.00 & 1.60 & 1.70 & 2.10 \\ 2.50 & 2.30 & 0.00 & 0.10 & 1.40 & 1.40 \end{bmatrix}.$$

Step 4: In the second round, the consensus degree of the decision-making representatives was -0.024498147569775024, which did not meet the consensus requirements. Subsequently, consensus adjustments were made based on the above scores, and after ten rounds of adjustments, focusing on the representative with the lowest consensus degree, a consensus level was reached, with a final consensus degree of 0.8019555217792464. This resulted in the final adjusted decision-making representative score matrix.

Step 5: According to prospect–regret theory and combined with the decision-making representative score matrix obtained above, as follows:

$$\begin{bmatrix} 89.00 & 77.67 & 41.65 & 106.23 & 46.32 \end{bmatrix}.$$

According to the final score matrix, the ranking of the final products is as follows:

$$x_4 \succ x_1 \succ x_2 \succ x_5 \succ x_3.$$

Drawing a brand score and ranking chart as shown in Figure 5, based on the above rankings and scores.

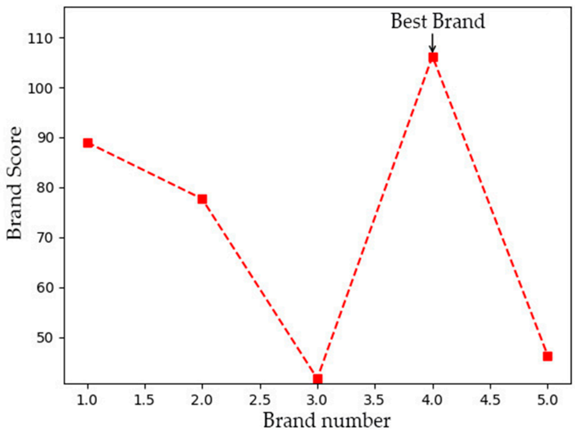

Figure 5. Our method ranks the comprehensive scores of the commodities.

Based on Figure 5 and the ranking, it can be concluded that BELAN's product is the best, after synthesizing the scores of six evaluation attributes for each solar light.

5.2. Advantages of Our Approach over Other Methods

In this section, the comparison will be divided into three parts: initially, we will delve into the significance and impact of the methodologies introduced in this paper for the purpose of decision-making. Secondly, we will undertake a comparative analysis using traditional multi-attribute decision-making techniques, including TOPSIS, TODIM, and VIKOR. Finally, a comparison by integrating the prospect–regret theory used in this paper with the above classic multi-attribute decision-making methods.

The corresponding methods and symbols used in this section are shown in Table 6.

Table 6. The comparison method corresponds to the symbolic diagram of the method representative.

Comparative Method	Method Symbol
Two-stage dual minimum consensus degree adjustment combined with the prospect–regret theory	m0
Remove the prospect–regret theory from m0	m1
Replace the prospect–regret theory in m0 with the prospect theory	m2
Replace the prospect–regret theory in m0 with the regret theory	m3
Classic multi-attribute decision-making method TOPSIS	m4
Classic multi-attribute decision-making method TODIM	m5
Classic multi-attribute decision-making method VIKOR	m6

Table 6. *Cont.*

Comparative Method	Method Symbol
Two-stage double minimum consensus degree adjustment combined with TOPSIS	m7
Two-stage double minimum consensus degree adjustment combined with TODIM	m8
Two-stage dual minimum consensus degree adjustment combined with VIKOR	m9

5.2.1. Compare Different Methods with Our Method

To clarify the impact of the important steps in the method proposed in this paper on decision-making outcomes, a comparison is made between the method used and its replacement methods during decision-making in m1 to m3. The focus is on three treatments of the prospect–regret theory proposed in this paper: removing the prospect–regret theory directly, replacing the prospect–regret theory with the prospect theory, and replacing the prospect–regret theory with the regret theory. The method m0 is compared with the replaced methods m1, m2, and m3, respectively. The experimental result graphs for these three treatments correspond to Figures 6a, 6b and 6c, respectively.

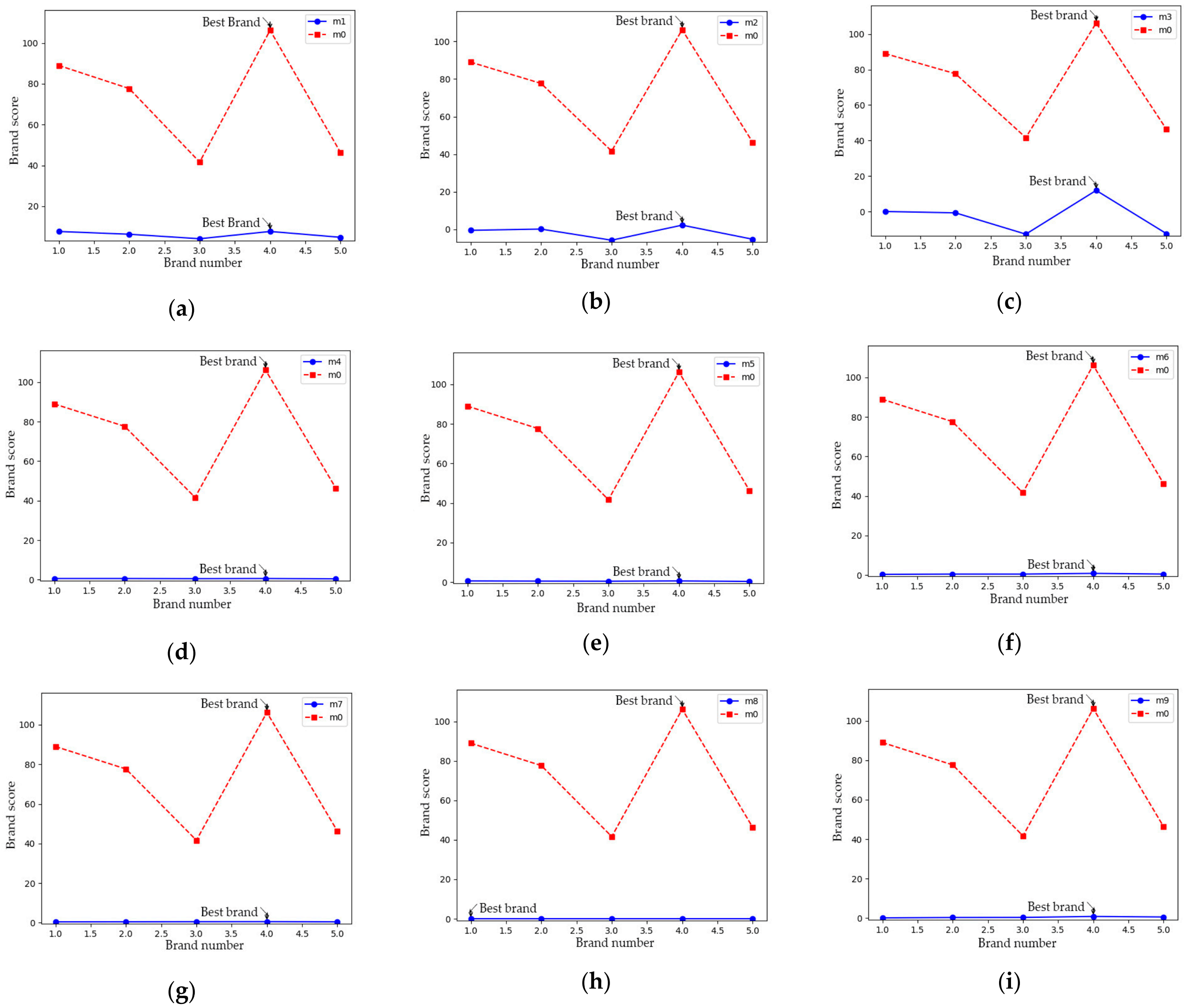

Figure 6. Comparison chart of this method with other methods.

To compare with the classic multi-attribute decision-making methods and identify the advantages of the method proposed in this paper, the classic multi-attribute decision-making methods TOPSIS, TODIM, and VIKOR are used for comparison, that is, method m0 is compared with classic methods m4, m5, and m6, respectively. The experimental result graphs obtained from the comparison correspond to Figures 6a, 6b and 6c, respectively.

To further control the variables, the two-stage minimum consensus-reaching process proposed in this paper is combined with the classic multi-attribute decision-making methods TOPSIS, TODIM, and VIKOR, respectively, and methods m7, m8, and m9 are compared with the method m0 proposed in this paper, respectively, in order to obtain more convincing comparative results.

It can be observed from figures a–i that the method proposed in this paper generally exhibits higher final product score differentiation compared to other methods. particularly in figures d–i, the product scores for methods m4 to m9 show overall less differentiation, whereas the scores obtained from our method have increased gaps, reducing the bias in final decision-making. moreover, the optimal brand selected by the method proposed in this paper aligns with the majority of other methods, except for a deviation with method m8 in figure h, which indicates the accuracy of the results produced by our proposed method.

According to the experimental results, it can be seen that the decision-making method proposed in this article is more conducive to producing decision outcomes. The significant differences between brands can effectively reduce user hesitation when choosing a brand and minimize deviations in selecting products. Moreover, the optimal product selected by the method proposed in this paper is basically consistent with the optimal product selected under the other decision-making methods, which also proves the correctness of this method for decision outcomes.

5.2.2. Similarity Analysis of Final Decision Outcomes Using Different Methods

This section presents two comparative experiments. Firstly, it compares the similarities between the sorting results of the method proposed in this article with those of the comparative methods, demonstrating that the method introduced in this paper aligns well with the decision-making outcomes. The results of this comparison are shown in Figure 7. Subsequently, it compares the final scores assigned to each product by the method proposed in this article with the scores assigned by the comparative methods. The results of this comparison are shown in Figure 8.

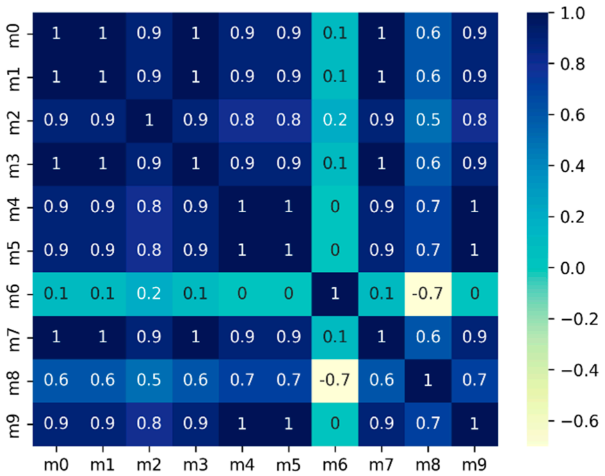

Figure 7. The Spearman's rank correlation plot of the similarity of product rankings.

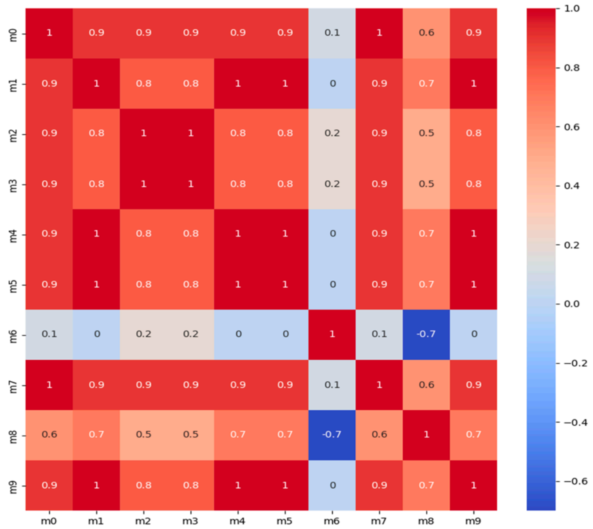

Figure 8. Spearman's rank correlation plot of product score similarity.

5.2.3. Analysis of Advantages Compared with Other Methods

To intuitively compare the advantages with other methods, comparisons were made in four aspects: the sentiment analysis, CRP, risk assessment, and classification ability. The comparison results are shown in Table 7.

Table 7. The advantages compared with other methods.

	Sentiment Analysis	CRP	Risk Assessment	Classification Ability	Accuracy
m1	√	√	×	√	×
m2	√	√	√	√	×
m3	√	√	√	√	×
m4	×	×	×	×	×
m5	×	×	×	×	×
m6	×	×	×	×	×
m7	×	×	×	√	×
m8	×	×	×	√	×
m9	×	×	×	√	×
m0	√	√	√	√	√

5.3. Performance Testing and Sensitivity Analysis

To enhance the practicality of the method, an analysis of its execution performance and sensitivity is conducted. The performance analysis includes the adjustment time when the decisions are made and the number of adjustment rounds for decision-makers. The sensitivity analysis mainly focuses on the parameters used in prospect–regret theory. By following these procedures, the merits of the method presented in this paper become even more evident.

5.3.1. Performance Analysis

As the decision-making process incorporates a growing number of experts, the CRP model introduced in this paper demonstrates its ability to swiftly converge on a consensus within a reasonable timeframe. Even when the number of experts balloons to 1000, the execution time remains under 70 s, as illustrated in Figure 9. This graphical representation highlights the efficient relationship between the number of decision-makers and the corresponding execution time. These findings underscore the practicality and dependability of the proposed method, particularly in scenarios where the decisions involve significant numbers of experts, extending into the thousands.

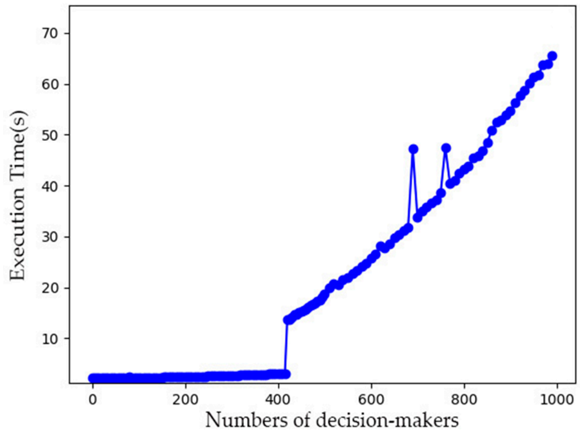

Figure 9. Performance analysis experimental chart.

The above simulation experiment was conducted using PyCharm Community Edition 2023.3.2, executed on a computer equipped with an Intel® Core™ i7-12700 processor from the 12th generation, with a running frequency of 3.90 GHz.

In order to ensure that within a certain range of decision-makers, the adjustment of the decision-maker scores can reach the required consensus level in a limited number of rounds, without the situation where consensus cannot be adjusted. The number of adjustment rounds for the least and second-least consensus degrees among 1000 decision-makers is counted. The results are shown in Figure 10 and Figure 11, respectively:

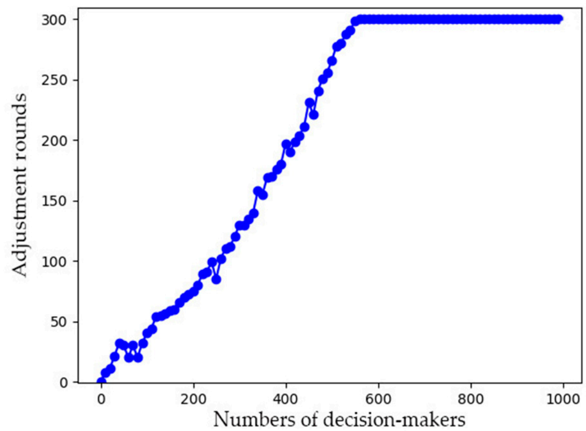

Figure 10. The number of adjusting rounds for the first minimum.

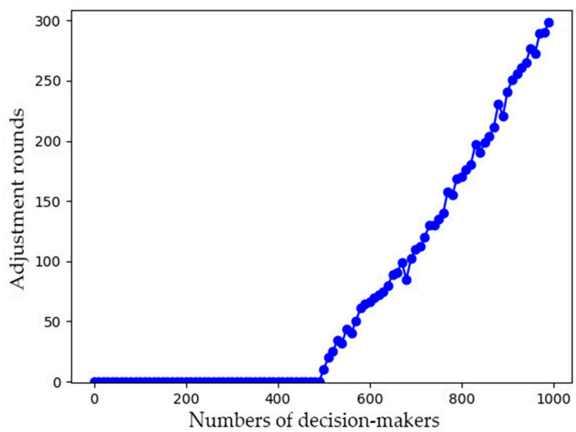

Figure 11. The number of adjusting rounds for the second.

5.3.2. Sensitivity Analysis

In this segment, the robustness of the proposed method is tested by conducting sensitivity analyses on the parameters α, β, and λ involved in the decision-making process.

In the content of the previous section, the value of α was set to 1.21. In this section, its value is set to 2.42 and 3.63, respectively. The ranking results of the goods under different values are shown in Table 8, and the sensitivity test results are shown in Figure 12.

Table 8. The sorting results when the parameters α take different values.

Parameter α Value	Sorting Result
$\alpha = 1.21$	$x_4 \succ x_1 \succ x_2 \succ x_5 \succ x_3$
$\alpha = 2.42$	$x_4 \succ x_1 \succ x_2 \succ x_5 \succ x_3$
$\alpha = 3.63$	$x_4 \succ x_1 \succ x_2 \succ x_5 \succ x_3$

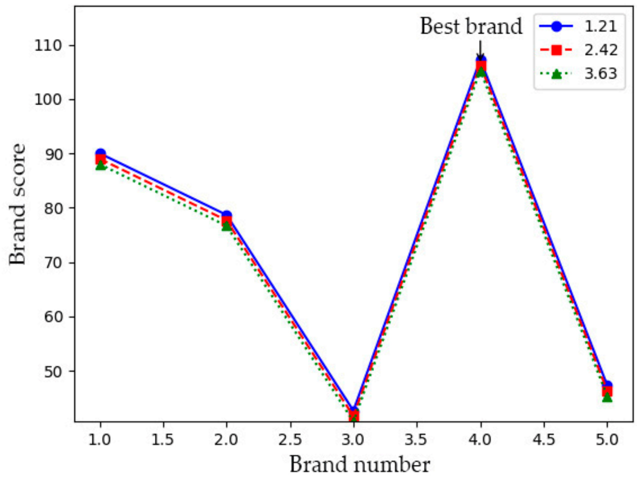

Figure 12. The sensitivity test for parameters α.

During the course of making a decision, the value of β is set to 1.02. To verify the stability of the results, its values are set to 2.04 and 3.06, respectively. The ranking results of the goods with different values are shown in Table 9, and the outcomes of the sensitivity analysis are presented in Figure 13.

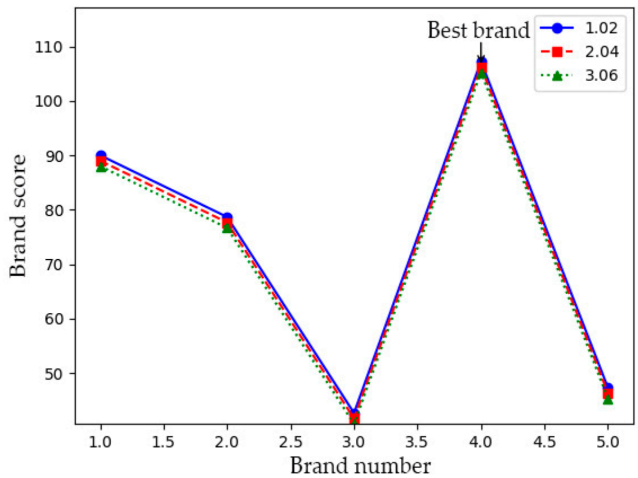

Figure 13. The sensitivity test for parameters β.

Table 9. The sorting results when the parameters β take different values.

Parameter β Value	Sorting Result
$\beta = 1.02$	$x_4 \succ x_1 \succ x_2 \succ x_5 \succ x_3$
$\beta = 2.04$	$x_4 \succ x_1 \succ x_2 \succ x_5 \succ x_3$
$\beta = 3.06$	$x_4 \succ x_1 \succ x_2 \succ x_5 \succ x_3$

During the calculation, the value of λ is taken as 2.25. In this section, its values are respectively taken as 4.5 and 6.75. The sorting results of the goods under different values are shown in Table 10, and the findings of the sensitivity test are depicted in Figure 14.

Table 10. The sorting results when the parameters λ take different values.

Parameter λ Value	Sorting Result
$\lambda = 2.25$	$x_4 \succ x_1 \succ x_2 \succ x_5 \succ x_3$
$\lambda = 4.5$	$x_4 \succ x_1 \succ x_2 \succ x_5 \succ x_3$
$\lambda = 6.75$	$x_4 \succ x_1 \succ x_2 \succ x_5 \succ x_3$

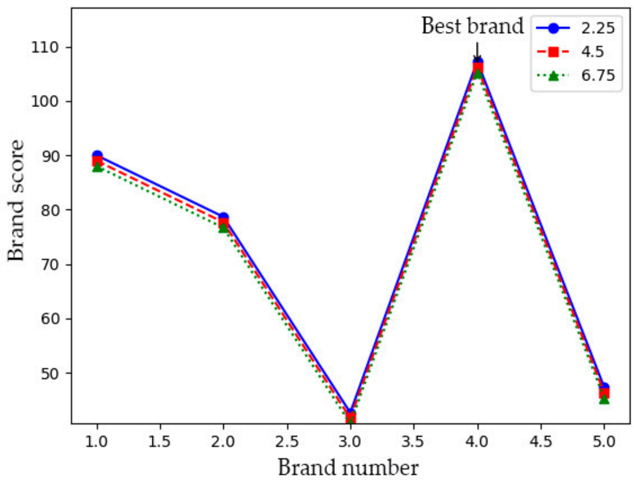

Figure 14. The sensitivity test for parameters λ.

6. Conclusions

This paper first converts the sentiments contained in online reviews into fuzzy numbers through the sentiment analysis. Next, it improves the Louvain algorithm using a mixed distance of Euclidean distances and Wasserstein distances. Then, a two-stage dual fine-tuning CRP model is used to adjust the scores of decision-makers. Additionally, the prospect–regret theory is utilized to address the potential joy and regret psychological issues that decision-makers might experience during the decision-making process. Ultimately, the model's applicability and operationality are confirmed via a case study involving the purchase of solar lights.

Considering the above analysis, the contributions of this paper are as follows:

(1) Incorporating a sentiment analysis into the LSGDM model to accurately quantify and analyze the fuzzy dataset of decision-makers' linguistic preferences.

(2) Using a mixed distance of Euclidean distances and Wasserstein distances to calculate the similarity between experts when constructing social networks based on the Louvain algorithm.

(3) Utilizing a two-stage process to reduce the decision scale while minimizing adjustments to decision-makers. Setting dual minimum consensus levels avoids multiple outlier situations and excessive adjustment times.

In future research, several aspects of the proposed method require further investigation to address its current limitations. First, the method lacks the capability to handle dynamically changing online review data effectively. Incorporating real-time monitoring and analysis processes is essential to adapt to continuous changes in review data. Techniques such as a time series analysis could explore trends and periodic changes, providing more timely and accurate information for decision-making. Second, the method does not adequately consider decision-makers' overconfidence during the CRP. Overconfidence can significantly influence decision outcomes, especially under uncertain conditions. A deeper analysis of how overconfidence affects the CRP is needed, focusing on how varying confidence levels among decision-makers impact consensus and decision quality. Addressing these limitations will enhance the method's robustness and applicability in real-world decision-making scenarios.

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Data Availability Statement: The dataset we used is already included in Appendix B at the end of the article.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Algorithm A1 is related to the methodological steps of Section 4.2.3, and it is the Louvain Algorithm.

Algorithm A1: The Louvain Community Clustering Algorithm Based on Mixed Distances

Input: The List of Fuzzy Number Matrices $|fuzzy\_numbers|$
Output: The Clustered Threshold Matrix
Loop i from 1 to $|fuzzy\_numbers|$:
  Loop for j from 1 to $|fuzzy\_numbers|$:
Calculate the Euclidean distance according to Formula (3)
end
Loop for i from 1 to $|fuzzy\_numbers|$:
  Loop for j from 1 to $|fuzzy\_numbers|$:
Calculate the Wasserstein distance according to Formula (12).
end
  Loop i from 1 to $|fuzzy\_numbers|$:
Loop for j from 1 to $|fuzzy\_numbers|$:
Calculate the comprehensive distances according to Formula (13).
  Add an edge connecting node i and node j in the weighted network graph G.
    Calculate the decision-makers' weights according to Formulas (16) and (17).
end
Final Result: Clustering Results

Algorithm A2 is related to the methodological steps of Section 4.3, and it is the CRP based on dual fine-tuning.

Algorithm A2: The CRP Based on Dual Fine-Tuning

Input: The decision group (containing scores of different decision-makers for different products), inter-group weights, intra-group weights
Output: The consensus decision representative score matrix
1 Initialize
2 Initialize attributes and brands with equal weights
3 Calculate the weight of each decision-makers for each attribute of each product, obtaining the weight matrix
4 while (var_g <parameter 1):
5 Calculate the average score matrix avg_g for each attribute of each product in each decision group
6 Calculate the variance var_g for each decision group according to Formula (18)
Remove decision-makers with larger variances:
7 Find the decision-makers with the largest variance
8 Remove the decision-makers from the decision group
9 end
10 Take the average score of the decision-makers as the decision representative score for that decision group, obtaining the decision representative score matrix w for all groups
11 Calculate the distances between each group leader and other group leaders according to Formula (19), obtaining the distance matrix dis
12 Calculate the consensus level of each group leader according to Formula (20), obtaining the consensus level matrix con
13 Calculate the group consensus level g_con according to Formula (21)
14 Find the group leader with the lowest consensus level
15 while ($g\_con <$ parameter 2 && the adjustment times for the group leader with the lowest consensus level are less than parameter 3):
16 Adjust the score of the group leader with the lowest consensus level using Formula (22)
17 Repeat steps 12–15
18 end
19 **while** ($g\_con <$ parameter 2)
20 Adjust the score of the group leader with the second lowest consensus level using Formula (22)
21 Repeat steps 12–14
22 end
23 **Final result:** The adjust decision representative score list W

Algorithm A3 is related to the methodological steps of Section 4.4, and it is the final scheme ranking decision based on the prospect–regret theory.

Algorithm A3: Final Scheme Ranking Decision Based on Prospect-Regret Theory

---

Input: Weight matrix, decision representative score matrix w
Output: Scheme ranking
1 Calculate the average value matrix of the score matrix w
2 Calculate the loss and gain matrix based on the average value matrix and the decision representative score matrix
3 Use Formula (5) from Section 3.4 to obtain the value function matrix V
4 Use Formula (6) from Section 3.4 to obtain the prospect value matrix pre
5 Compare the values in pre one by one to find max$V$ and min$V$
6 $d = \max V - \min V$
7 Use Formula (7) from Section 3.4 to calculate the joy value matrix P
8 Use Formula (8) from Section 3.4 to calculate the regret value matrix Q
9 Use Formula (9) from Section 3.4 to calculate the joy–regret matrix Re
10 Obtain the transpose matrix N of w
11 The comprehensive score is $Re \times N$
12 Rank the comprehensive scores
13 **Final result:** the scheme ranking from highest to lowest

---

Algorithm A4 is related to the LSGDM method based on double fine-tuning driven by online review data.

Algorithm A4: LSGDM Method Based on Double Fine-Tuning Driven by Online Review Data

Input: Fuzzy number matrix list, decision group (including different decision-makers' scores for different products), weight matrix
Output: Solution ranking

```
1  Initialize the fuzzy number dataset
2  Euclidean distance = calculate_euclidean_distance(fuzzy_number_set, metric = 'euclidean')
3  Wasserstein distance = create_zero_matrix(len(fuzzy_number_set), len(fuzzy_number_set))
4  for i in range(0, len(fuzzy_number_set) − 1):
5      for j in range(i + 1, len(fuzzy_number_set) − 1):
6          Wasserstein_distance[i][j] = calculate_wasserstein_distance(fuzzy_number_set[i], fuzzy_number_set[j])
7          Wasserstein_distance[j][i] = Wasserstein_distance[i][j]
8  Network graph = create_empty_graph()
9  for i in range(0, len(fuzzy_number_set) − 1):
10     for j in range(i + 1, len(fuzzy_number_set) − 1):
11         weight = (Euclidean_distance[i][j] + Wasserstein_distance[i][j])/2
12         add_edge(network_graph, i, j, weight)
13 Community division = detect_community_structure(network_graph, resolution = 0.85)
14 Community weights = {}
15 Total weight = calculate_sum_of_all_community_weights(community_division)
16 Initialize inter-group weights, intra-group weights, brand weights, and attribute weights
16 Initialize inter-group weights, intra-group weights, brand weights, and attribute weights
17 Weight result = calculate_weight(intra_group_weights, brand_weights, attribute_weights)
18 Average score = calculate_average(decision_group)
19 Variance result = calculate_variance(decision_group)
20 while (variance_result > parameter1):
21     remove decision maker with the highest variance
22     recalculate variance_result
23 Leader = average(decision_group)
24 Distance = calculate_distance(leader)
25 Consensus degree = calculate_consensus_degree(leader)
26 Group consensus degree = calculate_group_consensus_degree(leader, inter-group)
27 while (group_consensus_degree < parameter2 && adjustment_count < parameter3):
28     adjust leader's score
29     recalculate group_consensus_degree
30 If adjustment_count >= parameter3:
31     then use the second largest consensus degree
32     repeat steps 27–29
33 Calculate regret value matrix
32 Calculate delight–regret value matrix
33 Calculate transpose of the scoring matrix
34 Calculate comprehensive scoring matrix
35 Sort comprehensive scoring matrix
36 Output sorting results
36 Output sorting results
```

Appendix B

The data used in this section are as shown in the table below. It is defined that the final fuzzy number range for the product evaluation is from −3 to 3. In the table, each matrix represents a decision-making representative, and each row of it, respectively, represents a kind of product, which are "Xiang Zhe", "Shu Fu Jia", "Shuo Shi", "BELAN", and "You Chi" from top to bottom. Each column respectively represents different aspects of evaluation, which are the duration of light, price, appearance, service attitude, and product quality from left to right.

$\begin{bmatrix} 3.0 & 2.6 & 1.9 & 2.1 & 1.0 & 1.7 \\ 0.2 & 2.2 & 0.0 & 0.1 & 0.0 & 1.4 \\ 2.9 & 0.5 & 0.0 & 0.3 & 0.0 & 0.8 \\ 2.8 & 2.9 & 1.1 & 0.1 & 0.9 & 0.3 \\ 0.5 & 0.7 & 0.0 & 0.2 & 0.7 & -0.9 \end{bmatrix}$	$\begin{bmatrix} 0.5 & 0.7 & 0.0 & 0.2 & 0.7 & -0.9 \\ 0.1 & 0.0 & 0.1 & 1.3 & 0.0 & -0.1 \\ 2.8 & 1.9 & 0.1 & 2.6 & 0.2 & 2.3 \\ 1.4 & 1.9 & 0.2 & 0.3 & 0.3 & 0.0 \\ 2.5 & 2.5 & 0.2 & 0.8 & 0.0 & 2.1 \end{bmatrix}$
$\begin{bmatrix} 2.8 & 1.9 & 0.6 & 0.0 & 0.0 & 1.6 \\ 2.2 & -0.4 & 1.1 & 2.2 & 0.2 & 2.2 \\ 1.8 & 1.6 & 0.3 & 0.1 & 0.0 & 2.3 \\ 2.1 & 0.3 & 0.2 & 2.2 & 0.1 & 3.0 \\ 1.9 & 1.4 & 0.0 & 0.9 & 0.1 & 0.0 \end{bmatrix}$	$\begin{bmatrix} 2.1 & 2.5 & 0.0 & 0.4 & 0.2 & 1.8 \\ 1.9 & 0.0 & -0.1 & 0.6 & 0.2 & 2.2 \\ 2.3 & 2.5 & 0.0 & 1.6 & 0.1 & 2.9 \\ 1.9 & 2.2 & 0.0 & 1.8 & 0.1 & 2.4 \\ 2.2 & 0.4 & 0.0 & 0.1 & 0.2 & 1.1 \end{bmatrix}$
$\begin{bmatrix} 2.9 & 0.3 & 0.0 & 2.0 & 0.0 & 1.8 \\ 1.8 & 2.3 & 0.0 & 2.4 & 0.1 & 1.5 \\ -0.1 & 1.8 & 0.1 & 1.6 & 0.0 & 2.2 \\ 0.2 & 0.7 & 0.0 & 0.3 & 0.1 & 0.0 \\ 2.6 & 0.1 & 0.0 & 1.7 & 0.2 & 2.3 \end{bmatrix}$	$\begin{bmatrix} 0.5 & 1.8 & 0.0 & 2.3 & 0.1 & 1.6 \\ 2.4 & 0.8 & 0.2 & -0.3 & 0.0 & 0.1 \\ -0.2 & 0.5 & 2.6 & 1.6 & 0.1 & 2.3 \\ 0.2 & 2.1 & 0.0 & 0.4 & 0.1 & 1.6 \\ 0.2 & 0.4 & 0.0 & 1.5 & 0.1 & 0.3 \end{bmatrix}$
$\begin{bmatrix} 1.8 & 2.6 & 1.9 & 1.6 & 0.0 & 2.3 \\ 0.5 & 0.3 & 0.0 & 1.8 & 0.1 & 0.0 \\ 2.6 & 1.5 & 0.4 & 1.7 & 0.0 & 0.8 \\ 2.2 & 2.3 & 0.4 & 0.1 & 0.0 & 2.1 \\ 0.5 & 2.2 & 0.0 & 1.7 & 0.1 & 0.9 \end{bmatrix}$	$\begin{bmatrix} 0.1 & 0.8 & 0.0 & 1.8 & 2.5 & 2.3 \\ 2.5 & 0.3 & 0.1 & 1.2 & 0.0 & 2.1 \\ 1.8 & 0.3 & 2.1 & 1.6 & 0.0 & 2.3 \\ -0.2 & 0.0 & 1.5 & 0.1 & 2.3 & 0.1 \\ 0.1 & 0.0 & 1.6 & -0.3 & 0.0 & -0.1 \end{bmatrix}$
$\begin{bmatrix} 0.9 & -0.2 & 0.0 & 1.9 & 1.6 & 2.3 \\ 2.9 & 1.8 & 0.0 & 2.4 & 0.0 & 0.3 \\ 0.9 & 0.2 & 0.0 & 1.7 & 2.2 & 1.9 \\ 2.3 & 0.0 & 1.9 & 2.3 & 1.6 & 1.5 \\ 2.6 & 2.2 & 1.7 & 0.4 & 0.0 & 1.5 \end{bmatrix}$	$\begin{bmatrix} 2.4 & 0.4 & 0.0 & 0.2 & 0.0 & 2.1 \\ 2.2 & 2.9 & 1.3 & 0.0 & 1.8 & 1.6 \\ 1.5 & 2.2 & 0.1 & 0.0 & 0.0 & 1.4 \\ 2.2 & 0.0 & 1.4 & 0.1 & 1.7 & 2.5 \\ 2.8 & 0.8 & 1.6 & 1.4 & 0.7 & 0.9 \end{bmatrix}$
$\begin{bmatrix} 2.2 & 1.5 & 0.0 & 1.4 & 1.9 & 0.1 \\ 1.5 & 2.4 & 0.1 & 1.1 & 0.0 & 1.3 \\ 2.5 & 2.3 & 0.0 & 0.3 & 0.1 & 1.6 \\ 2.4 & 2.8 & 0.0 & 1.6 & 1.7 & 2.1 \\ 2.5 & 2.3 & 0.0 & 0.1 & 1.4 & 1.4 \end{bmatrix}$	$\begin{bmatrix} 2.8 & 2.6 & 1.9 & -0.1 & 1.0 & 1.7 \\ 0.2 & 1.0 & 0.8 & 1.9 & 0.3 & 1.4 \\ 2.9 & 0.5 & 0.0 & 0.3 & 1.2 & 0.8 \\ 2.8 & 1.6 & 0.4 & 0.1 & 0.8 & 0.3 \\ 0.5 & 0.7 & 0.1 & 0.2 & 0.7 & 0.8 \end{bmatrix}$
$\begin{bmatrix} 0.1 & 0.0 & 0.1 & 1.3 & 0.0 & -0.1 \\ 1.8 & 2.5 & 0.0 & 0.3 & 0.9 & 0.5 \\ 2.2 & 1.5 & 0.0 & 0.1 & 1.8 & 2.3 \\ 0.5 & 1.2 & 1.3 & 1.6 & 2.9 & -0.5 \\ 0.5 & 0.2 & 1.5 & 0.2 & 2.4 & 1.6 \end{bmatrix}$	$\begin{bmatrix} -0.9 & 1.4 & 2.8 & -0.9 & 0.5 & 1.3 \\ 0.9 & 0.3 & 2.6 & 2.4 & 1.9 & -0.6 \\ -0.9 & 2.6 & 2.8 & -2.6 & 0.2 & 2.3 \\ 0.3 & 0.9 & 0.7 & 0.6 & 2.9 & 0.0 \\ -1.5 & 2.5 & 0.2 & -2.4 & 1.4 & 2.1 \end{bmatrix}$
$\begin{bmatrix} -1.2 & 0.2 & 1.8 & 2.1 & 0.2 & 1.7 \\ 1.5 & 0.4 & 0.3 & 1.4 & 2.4 & -0.3 \\ 0.5 & 1.6 & 0.6 & 1.0 & 1.3 & 0.8 \\ 1.2 & 0.3 & -2.8 & -0.4 & 0.5 & 0.3 \\ 2.2 & 1.4 & 0.0 & 0.2 & 0.7 & 1.5 \end{bmatrix}$	$\begin{bmatrix} -0.6 & 2.5 & 1.4 & 2.7 & 1.9 & -0.6 \\ 2.0 & 0.3 & 0.9 & 1.4 & -0.5 & 1.2 \\ 0.4 & 1.8 & 1.5 & 0.8 & 1.7 & 0.7 \\ 1.5 & 1.2 & 1.9 & 2.7 & -0.2 & 0.0 \\ 0.2 & 0.3 & 1.4 & 0.6 & 2.7 & 1.1 \end{bmatrix}$
$\begin{bmatrix} 0.8 & 1.6 & 1.3 & 2.3 & 1.0 & 1.7 \\ 1.3 & 1.8 & 0.6 & 0.1 & 2.4 & 1.4 \\ 1.2 & 1.6 & 2.7 & 1.0 & 0.4 & 0.8 \\ 1.0 & 1.2 & 0.9 & 0.1 & 0.7 & 0.3 \\ 2.6 & 2.5 & 1.7 & 0.2 & 1.4 & -0.9 \end{bmatrix}$	$\begin{bmatrix} 2.7 & 2.1 & 1.9 & -1.8 & 0.7 & 0.8 \\ 0.1 & 2.5 & 2.3 & 1.7 & 0.0 & -0.1 \\ 2.7 & 0.4 & 0.1 & 2.6 & 1.6 & 2.2 \\ 1.4 & 2.8 & 0.2 & 1.3 & 0.3 & 0.7 \\ 2.5 & 2.1 & 0.0 & 0.8 & 0.0 & 2.1 \end{bmatrix}$
$\begin{bmatrix} 0.2 & 1.3 & 0.5 & 0.3 & 0.7 & 0.8 \\ -0.1 & 1.0 & -1.2 & 0.1 & 2.9 & 1.4 \\ 2.4 & 0.5 & 1.1 & 0.3 & 0.0 & -0.2 \\ 2.8 & 2.9 & 1.1 & 3.0 & 0.9 & 0.3 \\ 0.0 & 0.7 & 1.2 & 0.2 & 0.7 & 0.5 \end{bmatrix}$	$\begin{bmatrix} 2.9 & 0.2 & 0.5 & 0.2 & 0.7 & -0.9 \\ 0.1 & 1.7 & 0.4 & 1.3 & 0.0 & 0.6 \\ 2.2 & 1.9 & 0.1 & 1.6 & 0.2 & 2.3 \\ 2.1 & 2.6 & -0.1 & 0.3 & 1.3 & 2.7 \\ 1.9 & 1.8 & 0.2 & 0.8 & 0.0 & 2.1 \end{bmatrix}$
$\begin{bmatrix} 0.2 & 1.3 & 0.5 & 0.3 & 0.7 & 0.1 \\ 0.5 & 1.0 & 2.5 & 0.1 & 2.9 & 1.4 \\ 0.6 & 0.5 & 1.1 & 0.3 & 0.0 & -0.2 \\ 2.0 & 2.9 & 1.3 & -0.1 & 2.6 & 2.9 \\ 2.6 & 0.7 & 1.2 & 0.2 & 0.7 & 0.5 \end{bmatrix}$	$\begin{bmatrix} 0.3 & 0.2 & 0.5 & 0.2 & 0.7 & -0.9 \\ 0.1 & 0.4 & 1.2 & 1.5 & 0.0 & 0.6 \\ 2.2 & 1.9 & 0.1 & 1.6 & 0.2 & 2.3 \\ 2.1 & 2.0 & 1.8 & 2.5 & 1.3 & 2.7 \\ 1.6 & 2.0 & -0.1 & 0.8 & 0.0 & 1.5 \end{bmatrix}$

$\begin{bmatrix} 2.2 & 1.0 & -0.2 & 0.5 & 1.5 & 2.0 \\ 1.5 & 0.5 & 0.5 & 0.0 & 1.5 & 0.0 \\ 2.4 & 0.5 & 1.1 & 0.3 & 0.0 & -0.2 \\ 2.8 & 2.9 & 1.1 & 3.0 & 0.9 & 0.3 \\ 0.0 & 0.5 & 1.2 & 0.2 & 0.7 & 0.5 \end{bmatrix}$	$\begin{bmatrix} 2.9 & 0.2 & 0.5 & 0.2 & 0.7 & -0.9 \\ 0.1 & 1.7 & 0.4 & 1.3 & 0.0 & 0.6 \\ 2.2 & 1.9 & 0.1 & 1.6 & 0.2 & 2.3 \\ 2.1 & 2.6 & -0.1 & 0.3 & 1.3 & 2.7 \\ 1.9 & 1.8 & 0.2 & 0.8 & 0.0 & 2.1 \end{bmatrix}$
$\begin{bmatrix} 2.9 & 2.1 & 2.0 & 1.9 & 1.1 & 1.6 \\ 0.3 & 2.1 & 0.1 & -0.1 & 0.2 & 0.7 \\ 3.0 & 0.4 & -0.5 & 0.7 & 0.0 & 0.5 \\ 0.4 & 2.0 & 2.9 & 0.1 & 2.7 & 0.3 \\ 0.6 & 0.8 & -0.1 & 0.5 & 0.7 & -0.5 \end{bmatrix}$	$\begin{bmatrix} 0.6 & 0.4 & 0.5 & 1.0 & 0.0 & 0.1 \\ 0.5 & -0.1 & 0.5 & 0.8 & 0.0 & 1.4 \\ 2.4 & 1.7 & 0.1 & 0.9 & 0.5 & 2.5 \\ -0.1 & 1.9 & 1.2 & 2.3 & 0.3 & 2.5 \\ 2.1 & 2.5 & 0.9 & 0.5 & 0.0 & 2.6 \end{bmatrix}$
$\begin{bmatrix} 2.0 & 2.5 & 0.6 & 0.1 & 0.0 & 1.2 \\ 1.2 & 0.2 & 1.1 & 2.2 & 0.5 & 0.5 \\ 0.5 & 1.8 & 0.3 & 2.2 & 0.0 & 0.5 \\ 2.5 & 0.3 & 2.4 & 1.3 & 0.1 & 2.9 \\ 1.8 & 1.4 & 0.4 & 1.1 & 0.5 & 0.0 \end{bmatrix}$	$\begin{bmatrix} 2.6 & 1.2 & 0.0 & 0.5 & 0.2 & 1.0 \\ 1.9 & 1.4 & 0.5 & -0.1 & 0.5 & 1.2 \\ 2.3 & 2.1 & 0.0 & 1.6 & 0.1 & 2.9 \\ 1.9 & 2.2 & 0.0 & 1.8 & 2.0 & 2.9 \\ 0.5 & 0.4 & 2.3 & 0.1 & 0.2 & 1.1 \end{bmatrix}$
$\begin{bmatrix} 2.1 & 1.3 & 0.1 & 1.2 & 0.0 & 1.8 \\ 1.8 & 2.3 & 0.0 & 2.4 & 0.1 & 1.5 \\ 0.0 & -1.0 & 0.1 & 0.2 & 1.0 & 1.2 \\ 2.9 & 2.2 & 0.0 & 0.8 & 1.5 & 1.8 \\ 2.6 & 0.1 & 0.0 & 1.9 & 0.2 & 1.5 \end{bmatrix}$	$\begin{bmatrix} 0.8 & 1.5 & 0.0 & 1.5 & 0.1 & 0.5 \\ 2.4 & 0.8 & 0.2 & -0.3 & 0.0 & 0.1 \\ -0.2 & 0.4 & 1.5 & 1.6 & 1.4 & 2.3 \\ 1.0 & 2.4 & 0.0 & 0.4 & 0.8 & 1.8 \\ 0.2 & 1.0 & 0.0 & 2.4 & 0.1 & -0.1 \end{bmatrix}$

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