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# A novel online reviews-based decision-making framework to manage rating and textual reviews

Xiao-Hong Pan [a], Shi-Fan He [a,*], Diego García-Zamora [c], Ying-Ming Wang [b], Luis Martínez [c]

[a] School of Business, Qingdao University, Shandong, 266071, China
[b] Decision Sciences Institute, Fuzhou University, Fujian, 350108, China
[c] Department of Computer Science, University of Jaén, Jaén, 23071, Spain

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ABSTRACT

Rating and textual reviews are two of the most commonly used online reviews. However, most of existing studies utilize them separately to conduct decision analysis. Therefore, this paper proposes a novel Online Reviews-based Decision-Making (ORDM) framework that incorporates both kinds of reviews, which can effectively model and manage the inherent uncertainty and fuzziness in hybrid reviews. To do so, we first define a method to model hybrid online reviews as interval values. Then, an automatic Consensus-Reaching Process (CRP) developed from a novel Minimum Cost Consensus (MCC) model for interval values, is applied to obtain an agreed collective opinion. Finally, a new interval Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) method is defined to compare and rank alternatives. A case study is then presented to illustrate the feasibility of this approach. Additionally, sensitivity analysis and discussions are further conducted to discuss the influence of parameters and the superiority of the proposed method.

## 1. Introduction

The advancement of Web 2.0 and portable devices has facilitated the emergence of a massive online review ecosystem that enables virtual communication, information sharing, interoperability, and collaboration among users (Alonso et al., 2013; Jung & Suh, 2019; Yang et al., 2021). As a form of ‘electronic word-of-mouth’ communication, online reviews provide genuine evaluations and opinions of users about products, services, or events. Due to their independent and credible nature, online reviews are often considered a more reliable source of information than the providers of products or services (Zhang, Zhao, et al., 2020). Therefore, online reviews have become an indispensable information source in various fields, such as supply chain management (Huang et al., 2021), tourism management (Tsai et al., 2020), retailing and consumer services (Septianto et al., 2020), and so on.

Online reviews have the potential to empower decision-makers to make decisions based on ‘what they know’ from solid online review evidence rather than ‘what they think’ from subjective judgment (Shamim et al., 2019). Hence, utilizing online reviews to guide decision-making processes can significantly improve the accuracy of the results while reducing the influence of subjective factors. Consequently, Online Reviews-based Decision-Making (ORDM) is attracting increasing attention. Online rating reviews (Fan et al., 2018) and online textual reviews (Darko & Liang, 2022) are quite common online information used in decision-making. Specifically, online rating reviews typically use a simple five-star rating system to evaluate the products, services, or events, which is straightforward to use (Zhang, Zhao, et al., 2020). However, rating reviews may restrict the users’ freedom of expression and lack comment details about the products or services. On the other hand, online textual reviews allow users to express their opinions in further detail by natural language (He et al., 2022). Nevertheless, users tend to talk too much about specific aspects they like or dislike, which can lead to a deviation between their expressed views and their true views. Hence, a lot of online review platforms, such as Amazon,[1] Trip,[2] Jingdong,[3] Autohome[4] and so on, adopted hybrid online reviews combining both online rating reviews and online textual reviews, which can offer more comprehensive expression of users’ viewpoints and opinions.

* Corresponding author.
*E-mail addresses:* xiaohongpan0303@126.com (X.-H. Pan), shifanhe0828@163.com (S.-F. He), dgzamora@ujaen.es (D. García-Zamora), ymwang@fzu.edu.cn (Y.-M. Wang), martin@ujaen.es (L. Martínez).

1 https://www.amazon.com/
2 https://www.trip.com/
3 https://global.jd.com/
4 https://www.autohome.com.cn/

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**Nomenclature**

*Abbreviations*

| | |
|---|---|
| ORDM | Online Reviews-based Decision-Making |
| LSGDM | Large-Scale Group Decision-Making |
| TOPSIS | Technique for Order of Preference by Similarity to Ideal Solution |
| CRP | Consensus-Reaching Process |
| MCC | Minimum Cost Consensus |
| GDM | Group Decision Making |

*Symbols*

| | |
|---|---|
| $a_i$ | Alternative |
| $c_j$ | Criterion |
| $w_j$ | Weight of criterion $c_j$ |
| $v_k$ | Weight of expert/user |
| $co_k$ | Unit consensus cost of adjusting each expert's opinion |
| $D_i^+$ | The distance between alternatives and positive ideal solution |
| $D_i^-$ | The distance between alternatives and negative ideal solution |
| $\varepsilon$ | Maximum acceptable distance between individuals and collective opinion |
| $rr_{k,ij}$ | Online rating reviews |
| $tr_{k,ij}$ | Online textual reviews |
| $or_{k,ij}$ | Normalized rating reviews |
| $ot_{k,ij}$ | Sentiment score of textual reviews |
| $o_{k,ij}$ | Interval values transformed from online reviews |
| $CD_i$ | The closeness coefficient |
| $g$ | Collective opinion |
| $Dis(a,b)$ | The distance between $a$ and $b$ |
| $o_k$ | Original assessment of expert |
| $\mu$ | Consensus threshold |
| $x_{ij}$ | The evaluation assessment |
| $e_k$ | Expert/Effective reviews |
| $\bar{x}_{ij}$ | The normalized decision matrix |
| $nx_{ij}$ | The weighted normalized decision matrix |
| $nx_{ij}^+$ | The positive ideal solution for each criterion |
| $nx_{ij}^-$ | The negative ideal solution for each criterion |

To effectively employ hybrid online reviews, this paper proposes a novel ORDM framework, which models the uncertainty in users' reviews to better reflect their real views in decision-making. In this framework, the hybrid online reviews incorporating textual and rating reviews are processed into interval values. Moreover, a new information aggregation model and a novel alternative ranking method are proposed to deal with these interval values, which can avoid information loss as the outputs are still intervals. The contributions of this research are summarized as follows:

(1) The utilization of hybrid online reviews. Previous studies have primarily focused on either rating reviews or textual reviews (Darko & Liang, 2022; Fan et al., 2018), which may result in information loss and may not accurately represent the opinions of users. To address this limitation, this paper will utilize hybrid online reviews, incorporating both types of reviews as interval information, which can lead to a more comprehensive and accurate representation of users' opinions.
(2) A novel ORDM framework effectively managing interval information, including information aggregation and alternative ranking. Specifically, some existing ORDM research does not take all the available information into account when obtaining a collective opinion (He & Wang, 2023; Liu & Teng, 2019). In contrast, this research proposes a novel interval MCC model to effectively obtain a collective opinion close to each individual's real opinion. Besides, the classical TOPSIS method is extended using interval arithmetic, distances, and order relations to ensure that the hybrid online review information is not lost during the decision process (Bustince et al., 2013; Moore, 1979; Trindade et al., 2010).

The remainder of this paper is organized as follows. Section 2 presents a comprehensive literature review on Large-Scale Group Decision-Making, Minimum Cost Consensus models, and Online Reviews-based Decision-Making to establish a robust knowledge base. In Section 3, we introduce the proposed ORDM framework, which includes the description and transformation of hybrid online reviews, an automatic consensus model, and an interval TOPSIS method. Section 4 performs a case study to validate the proposed decision framework. In Section 5, a sensitivity analysis is conducted to test the influence of parameters on the decision and a discussion regarding the performance of the proposal is carried out in Section 6. Finally, the conclusions of this research are summarized in Section 7.

## 2. Literature review

To effectively utilize online reviews in decision-making, this paper aims to study the ORDM framework. To better clarify our research, a comprehensive literature review is presented in this section focusing on three key areas: Large-Scale Group Decision-Making, Minimum Cost Consensus models, and Online Reviews-based Decision-Making.

### 2.1. Large-scale group decision-making

Decision-making refers to the cognitive process of selecting a course of action from several alternatives, which is a frequent process in human daily life. However, some decisions require more reflection than one person's intuition. For this reason, decision science has emerged as a research line that attracts increasing attention (Saaty & Begicevic, 2010). As an important branch of decision science, Group Decision Making (GDM) is highlighted because a group of experts is involved in the decision process. The final decision made by GDM is no longer made by a single individual but is the responsibility of the whole group (Tang & Liao, 2021a). With the increasing complexity of decision-making scenarios and the development of internet technologies that made it easier to connect with experts regardless of time and space limitations, Large-Scale Group Decision-Making (LSGDM) is becoming increasingly popular. LSGDM typically arises in complex decision-making scenarios involving a large number of experts, each with their unique perspectives, preferences, and interests.

LSGDM offers a structured approach to effectively incorporate the individual preferences of a large group of experts when evaluating several alternatives based on multiple criteria (García-Zamora et al., 2022), which exhibit superiority in several key aspects. Firstly, it enables the inclusion of diverse perspectives, resulting in more comprehensive and informed decisions (Shi et al., 2018). Secondly, LSGDM leverages the collective wisdom of the crowd, leading to enhanced performance and better outcomes (Tang & Liao, 2021b). Lastly, in the face of increasing complexity in organizations and societies, involving a larger number of experts in decision-making becomes imperative to ensure a comprehensive consideration of all perspectives and interests (Song & Hu, 2019). Due to these advantages, LSGDM has found widespread application in various domains, including public policy-making (Wan et al., 2022), strategic planning (Zhou et al., 2022), public transportation (Zhang et al., 2021), and environmental impact assessments (Pan & Wang, 2021), and so on.

The general scheme of LSGDM is depicted in Fig. 1 (Chao et al., 2021). Given the involvement of a large number of experts, LSGDM

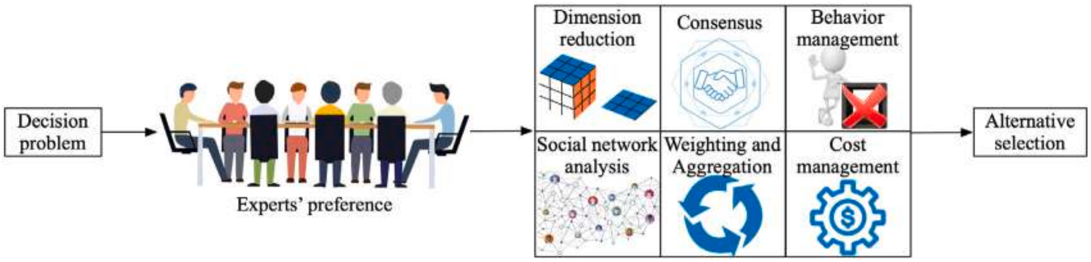


**Fig. 1.** General scheme of LSGDM.

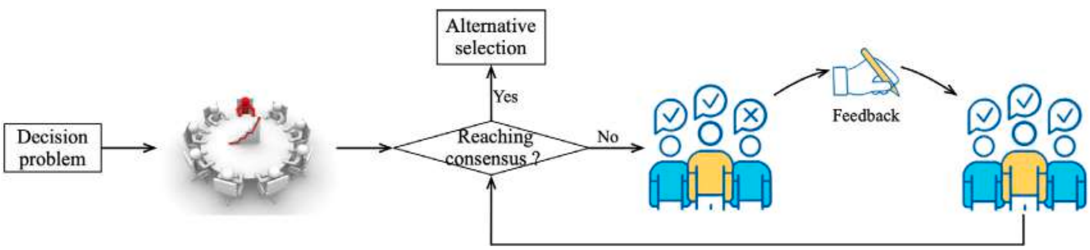


**Fig. 2.** General process of CRP.

faces new challenges in the decision-making process compared to traditional GDM (García-Zamora et al., 2022; Tang & Liao, 2021a). These challenges include: (1) Dimension reduction. This aspect aims to reduce the complexity and cost associated with LSGDM problems (Liu et al., 2020). (2) Consensus. As the number of participants in LSGDM grows, so does the potential for disagreement. Hence, it becomes crucial to measure consensus among large groups to facilitate reaching mutually agreed-upon solutions (Ji et al., 2023; Wang et al., 2024). (3) Behavior management. LSGDM needs mechanisms to handle non-cooperative experts and mitigate disharmonious relationships among them, ensuring productive collaboration (Chao et al., 2021; Palomares et al., 2013). (4) Social network analysis. This analytical approach considers the relationships between experts, such as trust, which can influence the decision process (Du et al., 2020; He et al., 2021). (5) Weighting and aggregation. These aspects pertain to effectively gauging the significance of the experts engaged in the decision-making process and efficiently fusing their opinions (Quesada et al., 2015). (6) Cost management. The interaction between experts and the moderator consumes considerable time and resources, requiring careful cost management within LSGDM frameworks (Liang et al., 2022; Rodríguez et al., 2021).

### 2.2. Minimum cost consensus models

Of note, in LSGDM, experts may provide different, conflicting, or polarized opinions due to their different interests, knowledge backgrounds, and thinking patterns. To ensure acceptance of decisions in an LSGDM problem, it is common to incorporate a Consensus-Reaching Process (CRP) that aims to mitigate conflicts among participants and soften the differences between their individual opinions (García-Zamora et al., 2022). As depicted in Fig. 2, this process usually entails a series of interactions and negotiations among experts, coordinated by a moderator. The moderator plays a crucial role in persuading experts to adjust their opinions, which may require investments such as time, resources, or effort (Cheng et al., 2022).

To facilitate CRP within LSGDM, moderators often deem it necessary to provide some form of compensation to the participating experts as a means to encourage them to adjust their opinions (Gong et al., 2023). In this endeavor, the moderator strives to achieve consensus while minimizing associated costs (Liao et al., 2022). Besides, in a decision situation in which a large number of experts are involved in a decision-making process, expecting them to reach a consensus through a discussion process becomes time-consuming, costly, and even unrealistic (García-Zamora et al., 2022). In such cases, automatic CRP models offer a solution or a guide to a solution by providing an agreed collective opinion automatically. Among various automatic CRP models, the Minimum Cost Consensus (MCC) models (Ben-Arieh & Easton, 2007) stand out as particularly suitable for solving LSGDM problems. This model offers the advantage of reformulating the consensus process as an optimization problem, enabling the attainment of an agreed solution within a few seconds (García-Zamora, Dutta, Massanet et al., 2023).

**Definition 1** (*Ben-Arieh & Easton, 2007*)**.** Let $E = \{e_1, \ldots, e_K\}$ represent the set of $K$ experts, $O = \{o_1, \ldots, o_K\}$ denote their original assessments, $X = \{x_1, \ldots, x_K\}$ indicate the adjusted assessments, and $C = \{c_1, \ldots, c_K\}$ signify the unit consensus cost associated with adjusting each expert's opinion. Then, the MCC model is defined as follows:

$$\begin{aligned} &\min \sum_{k=1}^{m} c_k |x_k - o_k| \\ &s.t.\ |x_k - g| \le \varepsilon, k = 1, \ldots, K. \end{aligned} \tag{1}$$

where $g$ represents the group collective opinion and $\varepsilon > 0$ is the maximum acceptable distance of each expert to the collective opinion.

The classic MCC model has been extended in various ways. For example, Zhang et al. (2011) investigated the impact of different aggregation operators used to derive the collective opinion on the solution of the optimization problem. Labella et al. (2020) explored the inclusion of an additional constraint related to the satisfaction of a specific consensus measurement. More recently, a fuzzy-based formulation for MCC models (García-Zamora, Dutta, Labella et al., 2023) has emerged as a versatile framework that enables the incorporation of additional constraints and diverse preference structures into MCC models. In general, when experts modify their initial opinions, there are two possible adjustment directions: upward adjustment and downward adjustment. Based on this idea, Cheng et al. (2018) proposed a MCC model under the context of asymmetric adjustment costs, where consensus costs are categorized into upward or downward adjustment directions. Furthermore, the MCC model has been integrated with other theories. Zhang, Dong et al. (2020) conducted a study based on game theory on consensus mechanisms with maximum return modification and minimum cost feedback. Du et al. (2022) combined minimum cost conflict risk mitigation with probabilistic linguistic information and developed an innovative failure mode and effect analysis model for

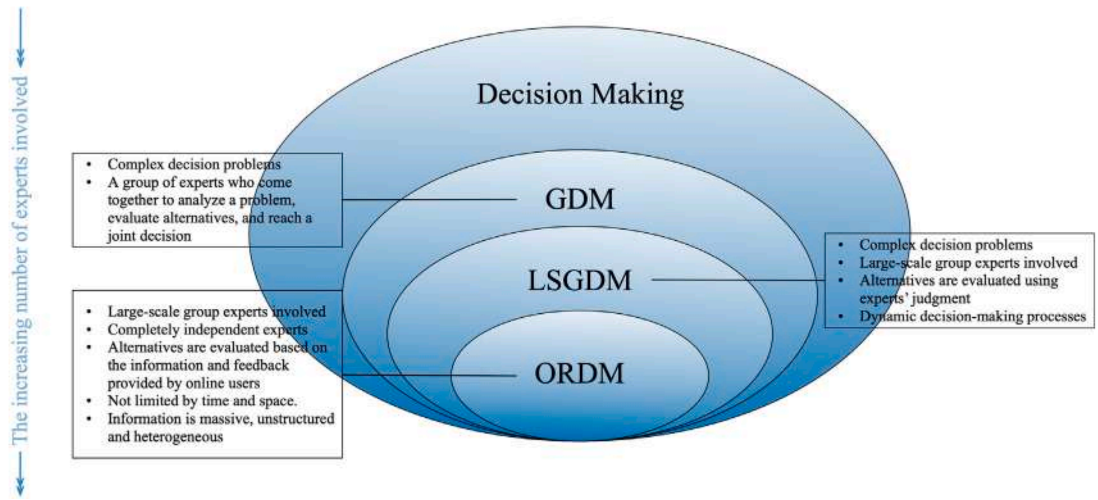


**Fig. 3.** Classification of GDM according to the number of experts involved.

risk assessment. Gong et al. (2021) introduced a consensus model that operates within a transaction and interaction framework, employing the Choquet integral in conjunction with the MCC model. However, there is a lack of interval MCC model, which cannot fully address situations involving interval values.

### 2.3. Online reviews-based decision-making

With the proliferation of Web 2.0, the preference information of LSGDM could not only be obtained by experts' judgments but also be automatically collected from online reviews, that is, Online Reviews-based Decision-Making (ORDM) (Chen et al., 2021; Fan et al., 2020; He et al., 2022). Online reviews contain the opinions and experiences of a large number of users, providing a valuable way to obtain the collective wisdom that reflects diverse perspectives and insights (Ji et al., 2023). This collective knowledge can be considered as experts' expertise in LSGDM. The relationship between GDM, LSGDM and ORDM is summarized in Fig. 3.

Online reviews are contributed by a large number of users with unique backgrounds, preferences, and experiences. This diversity enriches decision analysis by offering a range of perspectives, aiding in the formulation of informed decisions. However, the massive, and qualitative nature of online reviews makes them difficult to be directly used to make a decision. In this regard, it is necessary to propose useful methods for processing and leveraging this information in ORDM. According to the information used in decision-making, the current research in ORDM can be roughly classified into two categories: research focused on online rating reviews and those focused on online textual reviews.

For online rating reviews, some existing studies transform it as discrete probability distribution functions (Fan et al., 2018; Xia et al., 2020), or linguistic terms (Sharma et al., 2019; Zhang, Zhao, et al., 2020). (1) Transform rating reviews into discrete probability distribution functions. It is a function used in probability theory to describe discrete random variables, which are typically composed of two parts: the values and their corresponding probabilities. The values represent the specific numerical values the discrete random variable can take, while the probabilities represent the likelihood of each value occurring. Discrete probability distribution functions provide a powerful tool for understanding and quantifying online rating information. For instance, Fan et al. (2018) and Xia et al. (2020) transformed online rating reviews into discrete probability distribution functions. (2) Transform rating reviews into linguistic terms. Online rating reviews employ a five-star system, which can be regarded as a linguistic variable on a 1–5 scale. Specifically, 1 star=Very bad, 2 star = Bad, 3 star=Fair, 4 star = Good and 5 star =Very Good. For example, research conducted by Zhang, Zhao, et al. (2020) and Sharma et al. (2019) used linguistic terms to transform rating reviews.

For online textual reviews, existing studies primarily employ sentiment analysis to transform them into a score value (Bi et al., 2019; Joung & Kim, 2022, 2023), intuitionistic fuzzy sets (Li & Zhang, 2021; Liu et al., 2017; Zhang, Li, et al., 2020) or probabilistic linguistic term sets (Darko & Liang, 2022; Liang et al., 2021; Wu & Liao, 2021). (1) Transform textual reviews into score values. The sentiment strengths of online reviews reflect the users' perceptions of the product/service concerning the related criteria and can be regarded as their actual performances. For the convenience of further analysis, Bi et al. (2019) and Joung and Kim (2022, 2023) transformed them into score values based on the nominally coded data obtained from the sentiment analysis. (2) Transform textual reviews into intuitionistic fuzzy sets. Based on sentiment analysis results, online textual information can typically be categorized into positive, neutral, or negative sentiment categories, corresponding to the users' satisfaction, neutrality, or dissatisfaction with the subject being reviewed. These three aspects of sentiment categories correspond to the concepts of membership, hesitancy, and non-membership degrees in intuitionistic fuzzy sets (Liu et al., 2017). Therefore, intuitionistic fuzzy sets become one of the powerful tools for describing online textual information. For example, research conducted by Liu et al. (2017), Li and Zhang (2021), and Zhang, Li, et al. (2020) have all used intuitionistic fuzzy sets to process online textual information. (3) Transform textual reviews into probabilistic linguistic term sets. Probabilistic linguistic term sets have been proven to be a potentially effective tool for describing online information. On one hand, they allow for the expression of multi-level sentiment categories and their corresponding probability information, which can more accurately describe the emotions in online reviews than traditional "negative-neutral-positive" sentiment categories (Darko & Liang, 2022). On the other hand, probabilistic linguistic term sets do not require the sum of the probabilities of linguistic terms to be 1, making them capable of handling incomplete information (He et al., 2024). Therefore, probabilistic linguistic term sets are widely used for describing online textual information. For example, studies by Liu and Teng (2019), Wu and Liao (2021), and Liang et al. (2021) have all processed online textual reviews into probabilistic linguistic term sets.

However, some of the existing research is developed based on statistics-based methods, wherein all reviews are processed simultaneously and transformed into a single value. This approach may imply a loss of information, negatively affecting different properties of individual opinions and amplifying the impact of extreme opinions from individual users. To be specific, these methods fuse reviews with the

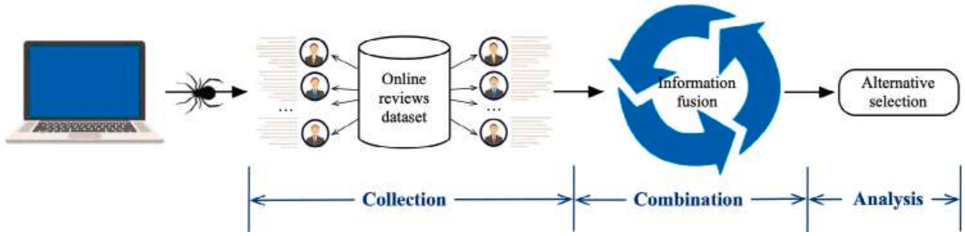


**Fig. 4.** General scheme of ORDM.

same sentiment level into one value. In reality, even reviews within the same sentiment level can have different sentiment scores. These statistics-based methods will ignore this difference and reduce the usefulness of online reviews.

## 3. A new ORDM framework using hybrid online reviews

ORDM refers to the process of making informed judgments or choices through the utilization of online reviews provided by users who have previously engaged with a product, service, or experience on digital platforms. It normally involves three phases-collection, combination, and analysis (see Fig. 4).

- Collection. The online reviews for each alternative are gathered from related websites by data crawling and processing technologies.
- Combination. The information within the individual reviews is aggregated to obtain a collective opinion about each product or service.
- Analysis. Decision-making methods are used to rank and select the best alternative based on the obtained information.

By employing online reviews, which are typically available on various websites, forums, social media platforms, or dedicated review platforms, decision-makers can access a wealth of firsthand experiences and opinions from a diverse range of sources. This allows them to gain insights into the strengths, weaknesses, advantages, and disadvantages associated with a specific item or alternative before making a well-informed decision.

This section proposes a novel ORDM framework that allows managing hybrid online reviews consisting of a rating and a piece of text. During the following subsections, the three main phases of the general ORDM scheme are developed. To carry out the collection phase, we develop a mechanism to conduct hybrid online reviews clawing, which are then processed and transformed into interval information. During the combination phase, we design an automatic CRP to guarantee that the interval collective opinion is close enough to all the individual reviews. Finally, the analysis phase is performed through a novel interval TOPSIS method. The flowchart of the proposed decision framework is depicted in Fig. 5.

### *3.1. The processing and transformation of hybrid online reviews*

Online reviews are a form of communication that is widely used on the Internet. It allows users to express their views, opinions, and suggestions on a variety of topics and content, providing valuable information to the online community and participants. Online ratings and textual reviews are two of the most commonly used types of online reviews. Online rating reviews normally use a simple five-star rating system to evaluate products, services, or events. Although it is straightforward and easy to use, it has several limitations.

(1) Firstly, online rating reviews ask users to use one-star, two-star, three-star, four-star, or five-star to express their opinions, which restricts the users' freedom of expression. For example, sometimes, users' real feelings may be between three and four stars, and online rating reviews cannot effectively express this situation.
(2) Secondly, online rating reviews lack detailed information and do not provide detailed review content. Typically, these reviews consist of a numerical rating without any accompanying explanations or elaborations. As a result, they fail to provide a comprehensive understanding of the users' experiences, preferences, and the specific factors that influenced their ratings.
(3) Finally, not all products, services, or events can be effectively expressed solely through online rating review information. For instance, when evaluating the user's opinion about a policy in their daily life, rating reviews may not adequately capture their nuanced viewpoints. Rating reviews are often suitable for simple, standardized products or services, but are not comprehensive or accurate for complex, highly personalized products or services.

Online textual reviews are a perfect supplement for online rating reviews. They can provide further detailed and rich review content, including the users' specific evaluation of the product or service, advantages, and disadvantages, use experience, feelings, etc. This information can better reflect the real opinions of the users and provide more valuable references and suggestions for decision-makers. However, sometimes, users tend to write too much about specific aspects they like or dislike, which leads to a deviation between their expressed views and their true views.

Hence, solely either rating reviews or textual reviews may not fully capture the opinions of users. To make the use of online review information as much as possible, this paper will use hybrid online reviews that consider both online rating and textual reviews. First, a sentiment analysis tool is used to transform the text reviews into a numeric value. Then, such numeric values and the rating reviews are normalized into the interval $[0,1]$, obtaining an interval delimited by the rating and textual reviews provided by each user.

Formally, the proposed processing and transformation method for hybrid online reviews is conducted as follows. Let us consider an ORDM problem to evaluate the alternatives $a_i (i = 1,\ldots,m)$. The reviews about the alternative $a_i$ are first gathered using data-crawling technology from related websites. Then, after data cleaning and duplication removal, effective reviews are kept, denoted as $e_{k,ij} (k = 1,\ldots,K_i; i = 1,\ldots,m; j = 1,\ldots,n)$, where $e_{k,ij}$ consists of $rr_{k,ij}$ for rating reviews and $tr_{k,ij}$ for textual reviews.

For online rating reviews, which are elicited in a numerical scale usually between 0 and 5, the score $or_{k,ij}$ of alternative $a_i$ under criterion $c_j$ of reviews $rr_{k,ij}$ is obtained by the following.

$$or_{k,ij} = rr_{k,ij}/5, k = 1,\ldots,K_i; i = 1,\ldots,m; j = 1,\ldots,n \tag{2}$$

where $or_{k,ij}$ is the normalized rating review, which is valued between 0 and 1.

For online textual reviews, a sentiment analysis process is carried out to mine the sentiment orientations of the alternatives regarding the criteria $c_j (j = 1,\ldots,n)$ from the online reviews $tr_{k,ij}$. By performing sentiment analysis, the sentiment score $ot_{k,ij}$ is obtained for

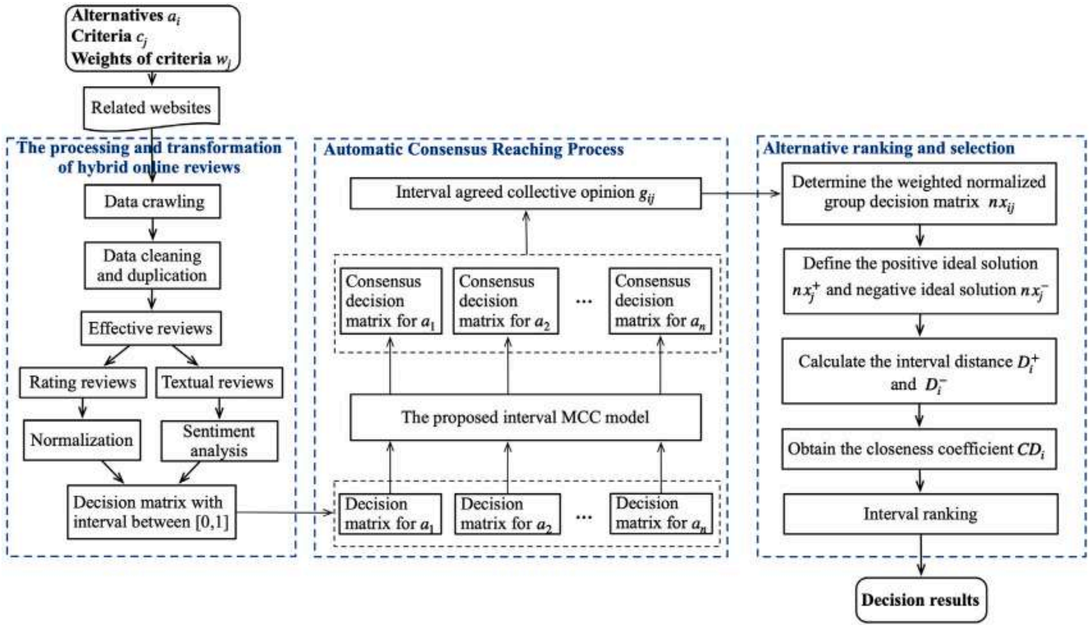


**Fig. 5.** The flowchart of the proposed decision framework.

each alternative $a_i$ under criterion $c_j$ based on the reviews $tr_{k,ij}$. This sentiment score is valued between 0 and 1, where higher scores indicate a more positive sentiment orientation and lower scores indicate a more negative sentiment orientation.

**Remark 1:** The sentiment analysis is used to analyze the sentiment or emotion usually expressed in a short text using various techniques. There are multiple sentiment analysis methods, which are suitable for different situations. In this paper, the utilized sentiment analysis methodology is based on SnowNLP.[5] It is an open-source Python library that offers tools for conducting sentiment analysis on Chinese text. SnowNLP utilizes natural language processing techniques including lexicon-based analysis and machine learning algorithms to analyze the sentiment of Chinese text, which has the advantage of simplicity, comprehensive functionality, and optimization for Chinese, making it fairly suitable for quick implementation and small projects.

Based on the rating score and sentiment score, we can transform hybrid online reviews into interval values by:

$$o_{k,ij} = [o^-_{k,ij}, o^+_{k,ij}] = \left[\min\{or_{k,ij}, ot_{k,ij}\}, \max\{or_{k,ij}, ot_{k,ij}\}\right] \tag{3}$$

Of note, the discrepancy between these two types of reviews reflects the inherent uncertainty in users' true opinions, which can be quantified by the length of the interval values. Generally, a longer interval length indicates a higher level of uncertainty in the reviews. Therefore, by utilizing interval values, we can more accurately depict the range of opinions and the level of uncertainty associated with them.

When using interval values, three aspects need to be noticed, i.e., the arithmetic algebra for interval values, the distance measure between interval values, and the order relation between interval values.

**(1) Arithmetic algebra for interval values**

Let $L([0,1]) = \{[a^-, a^+] | 0 \le a^- \le a^+ \le 1\}$ be the set of all closed subintervals of the unit interval. According to Moore's arithmetic algebra for interval values (Moore, 1979), for two non-negative interval values $a = [a^-, a^+], b = [b^-, b^+] \in L([0,1])$, we have

(1) $a + b = [a^- + b^-, a^+ + b^+]$
(2) $a - b = [a^- - b^+, a^+ - b^-]$
(3) $a \cdot b = [a^- \cdot b^-, a^+ \cdot b^+]$
(4) $a/b = [a^-/b^+, a^+/b^-]$, where $b^- \neq 0$
(5) $k \cdot a = [k \cdot a^-, k \cdot a^+], k > 0$.

Please note that the arithmetic rules provided here are specifically applicable to intervals in $L([0,1])$. For arithmetic rules pertaining to general intervals, please refer to Boche (1966).

**(2) Distance measure between interval values**

Most existing models for interval-valued distance produce a single value for interval values. As pointed out by Nakahara et al. (1992), the distance between two fuzzy numbers should comprise a value with varying degrees of membership, rather than a crisp value. Based on this idea, the distance measure proposed by Trindade et al. (2010) is more reasonable, which is defined as follows.

**Definition 2** (*Trindade et al., 2010*)**.** For $a = [a^-, a^+], b = [b^-, b^+] \in L([0,1])$, the distance between them can be defined as follows.

$$Dis(a,b) = \begin{cases} \begin{aligned}&\big[\min\{|b^- - a^+|, |a^- - b^+|\},\\ &\quad \max\{|b^- - a^+|, |a^- - b^+|\}\big],\end{aligned} & if\ a \cap b = \emptyset \\ \big[0, \max\{|b^- - a^+|, |a^- - b^+|\}\big], & if\ a \cap b \neq \emptyset \end{cases} \tag{4}$$

**(3) Admissible orders for intervals**

Even though there are many ranking methods for intervals in the literature, not all of them are based on total order relations. For instance, it is possible to rank intervals according to their center. However, in this case, different intervals with the same center will always be indistinguishable by such a ranking method. Therefore, total order relations play a crucial role when using interval values. Admissible orders are those total orders for intervals that extend the standard partial order in $\mathbb{R}^2$, which is defined as follows:

**Definition 3** (*Bustince et al., 2013*)**.** Let us consider a binary relation $\preceq$ defined on $L([0,1])$. Then, the $\preceq$ is an admissible order if

(1) $\preceq$ is a total order on $L([0,1])$,
(2) For intervals $[a^-, a^+], [b^-, b^+] \in L([0,1])$, $[a^-, a^+] \preceq [b^-, b^+]$ whenever $[a^-, a^+] \le_2 [b^-, b^+]$.

where $\le_2$ is the standard partial order of intervals, which is given by:

$$[a^-, a^+] \le_2 [b^-, b^+] \Leftrightarrow a^- \le b^- \wedge a^+ \le b^+. \tag{5}$$

[5] https://github.com/isnowfy/snownlp

**Example 1.** Some examples of admissible orders on $L([0,1])$ are (Bustince et al., 2013):

(1) Lexicographic 1: $[a^-, a^+] \preceq_{Lex1} [b^-, b^+] \Leftrightarrow a^- < b^-$ or ($a^- = b^-$ and $a^+ \leq b^+$);
(2) Lexicographic 2: $[a^-, a^+] \preceq_{Lex2} [b^-, b^+] \Leftrightarrow a^+ < b^+$ or ($a^+ = b^+$ and $a^- \leq b^-$);
(3) Xu–Yager: $[a^-, a^+] \preceq_{XY} [b^-, b^+] \Leftrightarrow a^- + a^+ < b^- + b^+$ or ($a^- + a^+ = b^- + b^+$ and $a^+ - a^- \leq b^+ - b^-$).

### 3.2. Automatic consensus-reaching process

When managing the opinions of large groups it is convenient to smooth out conflicts in the opinions to guarantee that the collective opinion properly represents all the individual preferences as much as possible (Chao et al., 2021; García-Zamora et al., 2022). Especially in ORDM, conflicts between reviews are prone to appear, and not managing them properly could lead to non-representative solutions that do not consider the perspectives of all the users (García-Zamora, Dutta, Massanet et al., 2023). In this context, the necessity of achieving agreed decisions becomes essential to provide robust and thoughtful solutions (García-Zamora, Labella et al., 2023). However, given the large number of users involved in online reviews, a classic CRP performing an iterative adjustment of their opinions is nearly impossible in practice not only because of limitations in time and cost but also because of the potential unavailability of the users (García-Zamora, Dutta, Labella et al., 2023). Consequently, using an automatic consensus model becomes mandatory in this case.

Among other automatic CRPs, MCC models are highlighted because of their capability to manage LSGDM problems with thousands of experts within a few seconds (García-Zamora, Labella et al., 2023). Of note, the idea behind MCC models is to automatically modify users' initial opinions so that the resulting collective preference is similar enough to all the individual modified opinions, by simultaneously minimizing the difference between original and modified preferences (Ben-Arieh & Easton, 2007; García-Zamora, Dutta, Massanet et al., 2023).

Since previous studies in MCC have not handled interval values effectively, this section proposes a novel MCC model able to manage interval values as inputs and outputs. Additionally, it must be emphasized that traditional LSGDM requires experts to evaluate all alternatives based on criteria. However, in the context of online reviews, this approach is unrealistic and could lead to information loss when making decisions, as only reviews from the same user are considered. In this paper, we propose a different approach to obtain a collective opinion. In our model, the consensus is reached independently on the different criteria for each alternative, by only considering the users who rate that alternative. This approach allows us to fully utilize the information provided by each user in the online reviews, resulting in more accurate and comprehensive decision-making. The details of the proposed model are as follows.

For each alternative $a_i (i = 1, \dots, m)$, we have $e_{k,ij}$ reviews about the $m$ alternative $a_i$ under $n$ criteria $c_j$. Each one of these reviews, which originally are given as a rating and a text, has been processed to be in the interval $o_{k,ij} = [o^-_{k,ij}, o^+_{k,ij}]$ where $k = 1, \dots, K_i$, $i = 1, \dots, m$, $j = 1, \dots, n$.

Then, the interval MCC model is given as:

$$\min \sum_{k=1}^{K_i} \sum_{j=1}^{n} \frac{1}{2} co_k w_j (Dis(x_{k,ij}, o_{k,ij})^+ + |Len(x_{k,ij}) - Len(o_{k,ij})|)$$
$$s.t. \begin{cases} x_{k,ij,1} \leq x_{k,ij,2} \quad \forall k = 1, \dots, K_i; i = 1, \dots, m; j = 1, \dots, n \\ g_{ij,t} = \sum_{k=1}^{K_i} v_k x_{k,ij,t} \quad \forall j = 1, \dots, n; t = 1, 2 \\ Dis^+(x_{k,ij}, g_{ij}) \leq \varepsilon, \quad \forall k = 1, \dots, K_i; j = 1, \dots, n \\ \sum_{k=1}^{K_i} \sum_{j=1}^{n} v_k w_j Dis(x_{k,ij}, g_{ij})^+ \leq 1 - \mu \end{cases} \tag{6}$$

where $w_j$ is the weight of criterion $c_j$ and $v_k$ is the weight of review $e_k$; $co_k$ is the unit consensus cost of adjusting each expert's opinion; $o_{k,ij}$ is the original evaluation assessment and $x_{k,ij} = [x^-_{k,ij}, x^+_{k,ij}]$ is the adjusted evaluation assessment, $x_{k,ij,1} = x^-_{k,ij}$ and $x_{k,ij,2} = x^+_{k,ij}$; $g_{ij}$ is the group collective evaluation assessment obtained according to individual evaluation assessment. $Dis(x_{k,ij}, o_{k,ij}) = [Dis(x_{k,ij}, o_{k,ij})^-, Dis(x_{k,ij}, o_{k,ij})^+]$ is the distance between original evaluation assessment and adjusted evaluation assessment, which can be obtained based on Eq. (4); $Len(x_{k,ij}) = x^+_{k,ij} - x^-_{k,ij}$ and $Len(o_{k,ij}) = o^+_{k,ij} - o^-_{k,ij}$ are the interval lengths for original evaluation assessments and adjusted evaluation assessments, respectively; $\varepsilon \in (0,1]$ is the maximum acceptable distance of each expert to the collective opinion; and $\mu \in [0,1)$ is the consensus threshold.

It must be highlighted that the model (Eq. (6)) receives interval values as inputs and produces interval values as outputs, without converting intervals to crisp numbers during the process. To do so, it has been defined by considering the rules for handling interval values that already exist in the literature. For instance, the collective opinion in this model is computed using the algebraic operations for interval values, whereas the distances between intervals are controlled by the classic interval distance.

Of note, although it is not explicit in the formulation for simplicity, the consensus conditions related to the parameters $\varepsilon$ and $\mu$, as well as the first sum in the objective function, are compatible with the Lexicographic 2 admissible order. Such order focuses on the upper bound of the intervals to rank them, which means that the bigger interval distances are those corresponding to the intervals containing the further values. We have exploited this property to improve the efficiency in the definition of the model (Eq. (6)): if we constraint the upper bounds of the interval distances to be lower than a certain numerical value, such as $\varepsilon$ or $\mu$, the lower bounds of the corresponding interval distances are also guaranteed to be lower than the same numerical value. This fact allows considerably improving the computational efficiency of the model (Eq. (6)), which is especially convenient for managing a large number of inputs simultaneously as in LSGDM problems (García-Zamora, Dutta, Massanet et al., 2023).

It should be noticed that nonlinear programming problems can be more complex and computationally expensive to solve than linear programming problems, especially as the complexity of the problem and the number of variables increase. In contrast, linear programming problems have well-established algorithms and can be solved efficiently. Therefore, we propose an equivalent linear version of the aforementioned model.

**Theorem 1.** *The model (Eq. (6)) can be linearized as follows:*

$$\min \frac{1}{2}(A + B)$$
$$s.t. \begin{cases} x_{k,ij,1} \leq x_{k,ij,2} \quad \forall k = 1, \dots, K_i, j = 1, \dots, n \\ g_{ij,t} = \sum_{k=1}^{K_i} v_k x_{k,ij,t} \quad \forall j = 1, \dots, n, t = 1, 2 \\ x_{k,ij,1} - o_{k,ij,2} = y_{k,ij,1}, \quad k = 1, \dots, K_i, j = 1, \dots, n \\ x_{k,ij,2} - o_{k,ij,1} = y_{k,ij,2}, \quad k = 1, \dots, K_i, j = 1, \dots, n \\ y_{k,ij,t} \leq Y_{k,ij}, \quad t = 1, 2, k = 1, \dots, K_i, j = 1, \dots, n \\ -y_{k,ij,t} \leq Y_{k,ij}, \quad t = 1, 2, k = 1, \dots, K_i, j = 1, \dots, n \\ x_{k,ij,1} - g_{ij,2} = z_{k,ij,1}, \quad k = 1, \dots, K_i, j = 1, \dots, n \\ x_{k,ij,2} - g_{ij,1} = z_{k,ij,2}, \quad k = 1, \dots, K_i, j = 1, \dots, n \\ z_{k,ij,t} \leq Z_{k,ij}, \quad t = 1, 2, k = 1, \dots, K_i, j = 1, \dots, n \\ -z_{k,ij,t} \leq Z_{k,ij}, \quad t = 1, 2, k = 1, \dots, K_i, j = 1, \dots, n \\ Z_{k,ij} \leq \varepsilon, \quad k = 1, \dots, K_i, j = 1, \dots, n \\ \sum_{k=1}^{K_i} \sum_{j=1}^{n} v_k w_j Z_{k,ij} \leq 1 - \mu \\ u_{k,ij} = x_{k,ij,2} - x_{k,ij,1} - (o_{k,ij,2} - o_{k,ij,1}) \quad \forall k = 1, \dots, K_i, j = 1, \dots, n \\ u_{k,ij} \leq U_{k,ij} \quad \forall k = 1, \dots, K_i, j = 1, \dots, n \\ -u_{k,ij} \leq U_{k,ij} \quad \forall k = 1, \dots, K_i, j = 1, \dots, n \\ \sum_{k=1}^{K_i} \sum_{j=1}^{n} co_k w_j Y_{k,ij} = A \\ \sum_{k=1}^{K_i} \sum_{j=1}^{n} co_k w_j U_{k,ij} = B \end{cases} \tag{7}$$

**Proof.** The proof is similar to the one shown by García-Zamora, Labella et al. (2023), taking into account that additional constraints are necessary to linearize the interval distances. □

### 3.3. Interval TOPSIS

TOPSIS method is a popular and easy-to-implement technique for solving multi-criteria decision-making problems. However, it has been limited to dealing with precise values and is unable to handle interval uncertainty. In response to this limitation, researchers have focused on developing the interval TOPSIS method (Ashtiani et al., 2009; Chu & Lin, 2009; Dymova et al., 2013; Jahanshahloo et al., 2009, 2006; Jiang et al., 2022; Pires et al., 2011; Tsaur, 2011; Yue, 2011), which extends the traditional approach to accommodate interval values and address uncertainty in decision-making processes. Despite these advancements, there are still certain limitations that need to be addressed in the existing interval TOPSIS literature.

(1) The information loss caused by uncertainty reduction methods. Several studies in the field have employed techniques to convert interval values into crisp values in the process of determining ideal solutions (Chu & Lin, 2009; Dymova et al., 2013; Jahanshahloo et al., 2006; Pires et al., 2011), in the process of calculating the distance between alternatives and ideal solutions (Jahanshahloo et al., 2009, 2006; Jiang et al., 2022; Tsaur, 2011; Yue, 2011), or in the process of obtaining relative closeness (Ashtiani et al., 2009). This may result in losing valuable information contained within the intervals.
(2) The way to determine positive and negative ideal solutions. In traditional TOPSIS, the positive and negative ideal solutions represent the logical best and worst alternatives available. Similarly, in interval TOPSIS (Ashtiani et al., 2009; Yue, 2011), the interval positive and negative ideal solutions should adhere to the same principle. Unfortunately, existing research on interval TOPSIS has approached this determination by subjective designation (such as $[1,1]$ for the positive ideal solution and $[0,0]$ for the negative ideal solution) (Ashtiani et al., 2009) or by the averaging of endpoints (Yue, 2011). These approaches lack a standardized and objective method for determining the interval positive and negative ideal solutions.
(3) The approach used to compare and rank interval values. Although some research obtaining ideal solutions or relative closeness as interval values, the way they compare and rank interval numbers cannot keep effectiveness because they compare and rank them based on their midpoint (Tsaur, 2011), or midpoint and half-width (Jahanshahloo et al., 2009). However, these interval ranking methods may prove to be invalid in certain scenarios, particularly when dealing with interval values that share the same center but differ in width.

To overcome these limitations and enhance the application of the TOPSIS method in ORDM, this section proposes a novel interval TOPSIS method. This method overcomes the issue of information loss by obtaining ideal solutions based on the evaluation, ensuring that interval information is preserved throughout the process. Both the input and output data in this method are represented as intervals, allowing for a more comprehensive analysis. Moreover, the interval ranking in the proposed method is based on the concept of admissible order, which has been demonstrated to be a valid approach for ranking intervals (Bustince et al., 2013; Zumelzu et al., 2022). The proposed Interval TOPSIS method consists of the following key steps:

**Step 1:** Determine the weighted normalized decision matrix $nx_{ij}$ using interval arithmetic.

$$nx_{ij} = [nx^-_{ij}, nx^+_{ij}] = w_j \cdot g_{ij} \tag{8}$$

where $w_j$ is the weight of criterion $c_j (j = 1, \ldots, n)$ and $g_{ij}$ is the collective opinion of alternative $a_i$ under criterion $c_j$.

**Step 2:** Define the positive ideal solution $nx^+_j$ and the negative ideal solution $nx^-_j$ for each criterion.

$$nx^+_j = \begin{cases} \max_{XY}\{nx_{ij} : i = 1, \ldots, m\}, & \text{if } c_j \text{ is benefit criterion} \\ \min_{XY}\{nx_{ij} : i = 1, \ldots, m\}, & \text{if } c_j \text{ is cost criterion} \end{cases} \tag{9}$$

$$nx^-_j = \begin{cases} \min_{XY}\{nx_{ij} : i = 1, \ldots, m\}, & \text{if } c_j \text{ is benefit criterion} \\ \max_{XY}\{nx_{ij} : i = 1, \ldots, m\}, & \text{if } c_j \text{ is cost criterion} \end{cases} \tag{10}$$

where $\max_{XY}$ and $\min_{XY}$ are obtained by the Xu–Yager admissible order defined before. In this case, the Xu–Yager admissible order ranks interval values by checking first the center of the interval. This is useful to rank interval values according to their "average" value.

**Step 3:** Calculate the distance between alternatives and positive ideal solution $D^+_i$, and the distance between alternatives and negative ideal solution $D^-_i$, respectively.

$$D^+_i = \sum_{j=1}^{n} Dis(nx_{ij}, nx^+_j) \tag{11}$$

$$D^-_i = \sum_{j=1}^{n} Dis(nx_{ij}, nx^-_j) \tag{12}$$

where $Dis(nx_{ij}, nx^+_j)$ and $Dis(nx_{ij}, nx^+_j)$ are obtained based on the interval distance given in Eq. (4).

**Step 4:** Obtain the closeness interval $CD_i$ of each alternative using interval arithmetic.

$$CD_i = \frac{1 - D^+_i + D^-_i}{2}, i = 1, \ldots, m \tag{13}$$

**Step 5:** Rank alternatives according to the closeness interval based on the XY admissible order. The larger the closeness interval, the better the alternative will be.

## 4. Case study

User-generated information is now easily accessible and has become a valuable resource for decision-making due to the emergence of various online platforms and the advancement of information technology. This is especially useful for highly competitive and dynamic service industries as it is cost-effective and highly accessible. In this section, we aim to demonstrate the applicability and superiority of the proposed decision framework through a case study of automobile evaluation. Specifically, we will assist automobile manufacturers in conducting comprehensive evaluations of their vehicle performance, in which alternatives are denoted as $z_1$, $z_2$, $z_3$, and $z_4$ (names have been withheld to avoid influencing consumer preferences).

### 4.1. Data acquisition

We have collected a dataset of hybrid online reviews about these four alternatives from the website pcauto,[6] which is a professional automotive network media platform that offers an interactive communication platform. The dataset consists of online rating reviews and textual reviews during the past two years, between January 1st, 2021 and January 1st, 2023. As shown in Fig. 6, the website provides a structured format for reviews, requiring the reviewer to comment on eight aspects: Appearance, Interior, Space, Cost performance, Power, Control, Gas mileage, and Comfortability, denoted as $c_1$, $c_2$, $c_3$, $c_4$, $c_5$, $c_6$, $c_7$ and $c_8$, respectively. Without loss of generality, the weights of these criteria and the weights of reviews are assumed to be the same in the paper, which are $w_j = \frac{1}{n}$ and $v_k = \frac{1}{K_i}$, $k = 1, \ldots, K_i$.

Once the hybrid reviews were collected, data cleaning and preprocessing were performed to eliminate duplicates and useless reviews. This was achieved through the following rules:

(1) Duplicated comments were identified by comparing the user identifier, comment time, and comments for all aspects. If these were identical, the comment was considered a duplicate and removed.

[6] https://www.pcauto.com.cn/

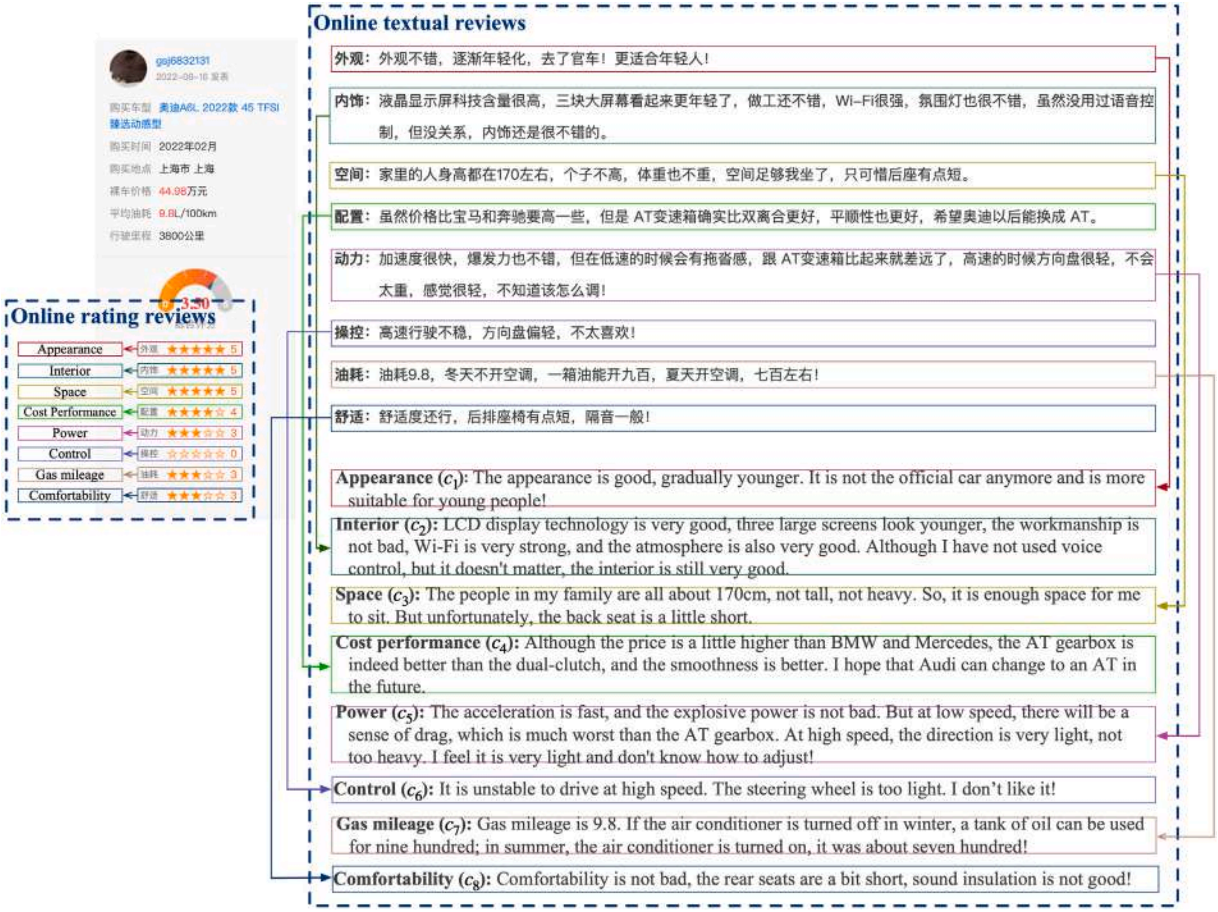


**Fig. 6.** Example of online reviews in the website pcauto.

**Table 1**
Overall information of the obtained online reviews.

| | | | | | | |
|---|---|---|---|---|---|---|
| Alternatives | | | 4 | | | |
| Criteria | | | 8 | | | |
| Comment time span | | | 2021/1/1-2023/1/1 | | | |
| Reviews | $z_1$ | Original | 387 | $z_3$ | Original | 225 |
| | | Preprocessed | 365 | | Preprocessed | 164 |
| | $z_2$ | Original | 351 | $z_4$ | Original | 221 |
| | | Preprocessed | 245 | | Preprocessed | 143 |

(2) Useless comments were identified as those with blank contents for textual reviews or a rating of 0 for rating reviews. These were deemed useless and excluded.

Then, Table 1 provides an overview of the obtained hybrid online reviews. Detailed comments can be found online.[7]

### 4.2. Decision process

Employing the proposed ORDM framework to deal with this evaluation problem mainly involves the following steps:

**Step 1:** Obtain online reviews by data-crawling technology from related websites and preprocess them by data cleaning and duplication. Then, effective reviews are kept, which are available online.

**Step 2:** Process online rating and textual reviews into $[0,1]$ by the normalization based on Eq. (2) and sentiment analysis respectively.

**Step 3:** Construct original evaluation assessment according to interval values consisting of rating score and sentiment score based on Eq. (3).

**Step 4:** Apply the model (Eq. (6)) in each alternative to get a collectively agreed opinion. Here, the parameters are set as $\varepsilon = 0.2, \mu = 0.8$.

**Step 5:** Obtain the interval decision matrix containing the collective evaluations for all the alternatives and criteria, which is shown in Table 2.

**Step 7:** Determine the weighted normalized decision matrix $nx_{ij}$ based on Eq. (8), which is shown in Table 3.

**Step 8:** Define the positive ideal solution $nx_j^+$ and the negative ideal solution $nx_j^-$ for each criterion based on Eq. (9) and Eq. (10) respectively. Note that $c_7$ is cost criteria, and other criteria are benefit criteria. The results are shown in Table 4.

**Step 9:** Calculate the distance between alternatives and positive ideal solution $D_i^+$ based on Eq. (11), and the distance between alternatives and negative ideal solution $D_i^-$ based on Eq. (12), respectively. The results are shown in Table 5.

[7] Vehicle HOR(2021–2023) dataset: https://github.com/Shifan-He/Vehicle-HOR-2021-2023-dataset.

**Table 2**
The group collective opinion.

| | $z_1$ | $z_2$ | $z_3$ | $z_4$ |
|---|---|---|---|---|
| $c_1$ | [0.919,0.957] | [0.925,0.970] | [0.956,0.980] | [0.938,0.975] |
| $c_2$ | [0.803,0.875] | [0.864,0.921] | [0.886,0.940] | [0.846,0.924] |
| $c_3$ | [0.761,0.827] | [0.809,0.875] | [0.784,0.844] | [0.792,0.872] |
| $c_4$ | [0.878,0.936] | [0.874,0.937] | [0.900,0.957] | [0.895,0.962] |
| $c_5$ | [0.848,0.908] | [0.844,0.901] | [0.871,0.933] | [0.872,0.940] |
| $c_6$ | [0.855,0.921] | [0.828,0.896] | [0.887,0.943] | [0.828,0.906] |
| $c_7$ | [0.543,0.575] | [0.526,0.545] | [0.623,0.672] | [0.639,0.686] |
| $c_8$ | [0.762,0.823] | [0.807,0.868] | [0.829,0.888] | [0.865,0.936] |

**Table 3**
The weighted normalized decision matrix.

| | $z_1$ | $z_2$ | $z_3$ | $z_4$ |
|---|---|---|---|---|
| $c_1$ | [0.115,0.120] | [0.116,0.121] | [0.120,0.123] | [0.117,0.122] |
| $c_2$ | [0.100,0.109] | [0.108,0.115] | [0.111,0.118] | [0.106,0.116] |
| $c_3$ | [0.095,0.103] | [0.101,0.109] | [0.098,0.105] | [0.099,0.109] |
| $c_4$ | [0.110,0.117] | [0.109,0.117] | [0.112,0.120] | [0.112,0.120] |
| $c_5$ | [0.106,0.114] | [0.105,0.113] | [0.109,0.117] | [0.109,0.118] |
| $c_6$ | [0.107,0.115] | [0.104,0.112] | [0.111,0.118] | [0.103,0.113] |
| $c_7$ | [0.068,0.072] | [0.066,0.068] | [0.078,0.084] | [0.080,0.086] |
| $c_8$ | [0.095,0.103] | [0.101,0.109] | [0.104,0.111] | [0.108,0.117] |

**Table 4**
The positive ideal solution and negative ideal solution.

| | Positive ideal solution | Negative ideal solution |
|---|---|---|
| $c_1$ | [0.120,0.123] | [0.115,0.120] |
| $c_2$ | [0.111,0.118] | [0.100,0.109] |
| $c_3$ | [0.101,0.109] | [0.095,0.103] |
| $c_4$ | [0.112,0.120] | [0.109,0.117] |
| $c_5$ | [0.109,0.118] | [0.105,0.113] |
| $c_6$ | [0.111,0.118] | [0.104,0.112] |
| $c_7$ | [0.066,0.068] | [0.080,0.086] |
| $c_8$ | [0.108,0.117] | [0.095,0.103] |

**Step 10:** Obtain the closeness coefficient $CD_i$ of each alternative based on Eq. (13) as $CD_1 = [0.4535, 0.5345]$, $CD_2 = [0.4655, 0.5465]$, $CD_3 = [0.4635, 0.5435]$, and $CD_4 = [0.458, 0.543]$.

**Step 11:** Rank alternatives according to the closeness coefficient based on the Lexicographic 1 admissible order. Then, we have $z_2 \succ z_3 \succ z_4 \succ z_1$. The larger the closeness coefficient, the better the alternative will be. Hence, alternative $z_2$ is the best alternative.

## 5. Sensitivity analysis

When employing the proposed decision framework, two parameters should be considered and decided, i.e., the maximum acceptable distance of each expert to the collective opinion $\varepsilon$ and the consensus threshold $\mu$. To test their influences on the decisions, a sensitivity analysis is conducted by considering two different scenarios.

Scenario 1: Keep the values of $\mu$ unchanged, and change the value of $\varepsilon$ from 0 to 1 with the step of 0.01. The decision results are shown in Fig. 7.

Scenario 2: Keep the values of $\varepsilon$ unchanged, and change the value of $\mu$ from 0 to 1 with the step of 0.01. The decision results are shown in Fig. 8.

We can observe that the values of parameters will affect the decision results. Fig. 7 and Fig. 8 illustrate that the parameters $\varepsilon$ and $\mu$ have an influence on the decision results, although they generally produce relatively stable results. In Fig. 7, it can be noticed that the ranking order of alternatives will change with the change of parameter $\varepsilon$, but $z_4$ consistently remains the worst alternative. Fig. 8 shows that the ranking of alternatives remains stable until $\mu$ reaches 0.85. This indicates that for this decision problem, when $\mu \le 0.85$, there is no need to adjust user opinions; however, when $\mu > 0.85$, user opinions should be adjusted. Of note, for different decision problems, parameters should be set according to specific situations.

- Parameter $\varepsilon$ controls the maximum acceptable distance of each expert to the collective opinion. Normally speaking, the larger the value is, the higher the possibility that the collective opinion is accepted by all individuals. For decision problems that have time or cost limitations, a lower value of $\varepsilon$ may be preferable.
- Parameter $\mu$ represents the consensus threshold, which is a predefined value used to determine the level of agreement required among individuals within the group to reach a consensus decision. A larger value of $\mu$ indicates a higher requirement on consensus. In situations demanding strong consensus, a higher value of $\mu$ should be adopted.

## 6. Discussion

This section aims to demonstrate the superiority of the proposed ORDM framework from three perspectives: (1) the utilization of hybrid online reviews, (2) the superiority of employing interval MCC model to obtain collective opinion and (3) the management of interval uncertainty. Besides, management implications are also provided to further explore the practical relevance of the proposed decision framework.

### 6.1. The utilization of hybrid online reviews

The existing research primarily focuses on two aspects: online rating reviews (Fan et al., 2018) and online textual reviews (Darko & Liang, 2022; Zhang, Li, et al., 2020). As previously mentioned, online rating reviews often fail to effectively capture users' opinions because they only provide a five-star rating system, while online textual reviews may exhibit bias as users tend to elaborate extensively on specific aspects they either like or dislike. In contrast, this study concentrates on hybrid online reviews, combining both rating and textual reviews to comprehensively harness online reviews. To demonstrate the advantages of utilizing hybrid online reviews, we conduct a comparative analysis by employing the proposed decision analysis based separately on online rating reviews and online textual reviews. To ensure fairness in comparison, the same dataset- Vehicle HOR(2021–2023)[8] will be utilized, which includes both rating and textual review information.

(1) Utilization of online rating reviews

First, reach consensus and obtain group collective opinion based on the proposed automatic consensus model. Here, the parameters are set as before. Then, by applying the proposed interval TOPSIS method, the closeness coefficient $CD_i$ of each alternative is obtained, which are $CD_1 = 0.483$, $CD_2 = 0.514$, $CD_3 = 0.502$, and $CD_4 = 0.506$. Based on the closeness coefficient, we can rank alternatives as $z_2 \succ z_4 \succ z_3 \succ z_1$. Hence, alternative $z_2$ is the best alternative.

(2) Utilization of online textual reviews

First, reach consensus and obtain group collective opinion based on the proposed automatic consensus model. Here, the parameters are set as before. Then, by applying the proposed interval TOPSIS method, the closeness coefficient $CD_i$ of each alternative is obtained, which are $CD_1 = 0.491$, $CD_2 = 0.496$, $CD_3 = 0.513$, and $CD_4 = 0.505$. Based on the closeness coefficient, we can rank alternatives as $z_3 \succ z_4 \succ z_2 \succ z_1$. The larger the closeness coefficient, the better the alternative will be. Hence, alternative $z_3$ is the best alternative.

In summary, the decision results obtained by utilizing rating reviews are $z_2 \succ z_4 \succ z_3 \succ z_1$, the decision results obtained by utilizing textual reviews are $z_3 \succ z_4 \succ z_2 \succ z_1$, and the decision results obtained by utilizing hybrid reviews are $z_2 \succ z_3 \succ z_4 \succ z_1$. From the results, we can intuitively notice that the decision results obtained by using different forms of online reviews are different. The reason for this difference is the employment of different kinds of information. For the same decision problem, the decision relying solely on rating reviews or textual reviews may lead to unreliable results due to their incomplete nature. For

[8] https://github.com/Shifan-He/Vehicle-HOR-2021-2023-dataset

**Table 5**
The positive ideal solution and negative ideal solution.

| | $z_1$ | $z_2$ | $z_3$ | $z_4$ |
|---|---|---|---|---|
| Distance between alternatives and positive ideal solution $D_i^+$ | [0.007,0.100] | [0.000,0.081] | [0.010,0.076] | [0.012,0.088] |
| Distance between alternatives and negative ideal solution $D_i^-$ | [0.008,0.075] | [0.012,0.092] | [0.002,0.095] | [0.005,0.097] |

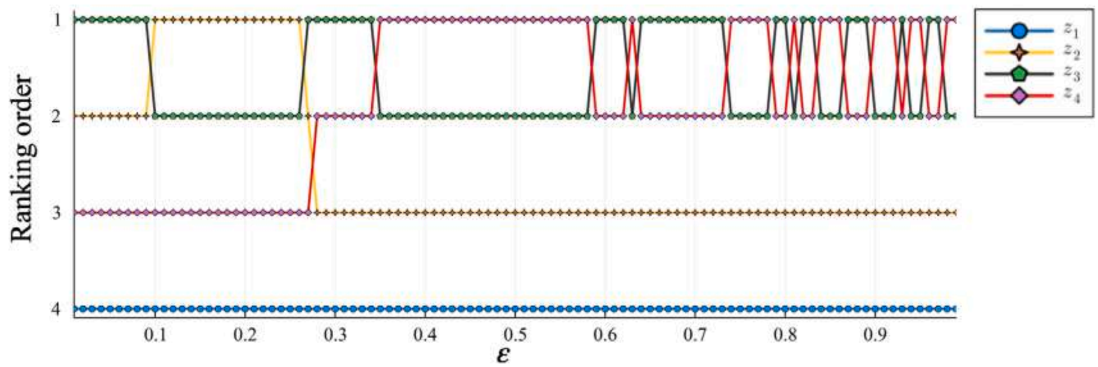


**Fig. 7.** Decision results obtained by different $\varepsilon$.

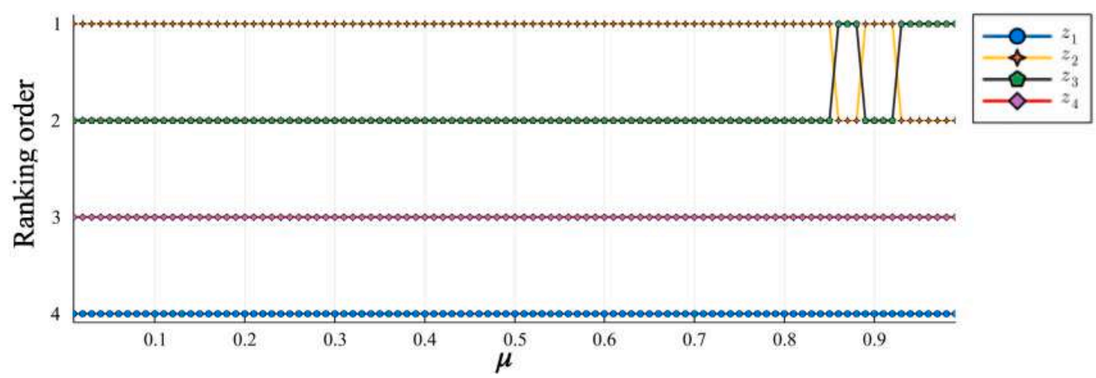


**Fig. 8.** Decision results obtained by different $\mu$.

instance, rating reviews may restrict users' freedom of expression and lack details about the products or services, while textual reviews may contain too much content about specific aspects users like or dislike, which can lead to a deviation between their expressed views and their true views. In contrast, the use of hybrid online reviews can provide a more comprehensive view of the evaluated products or services, leading to a more accurate and reliable assessment of their performance.

### *6.2. The superiority of employing interval MCC model to obtain collective opinion*

The qualitative nature of online reviews together with the massive number of them makes them difficult to be directly used to make a decision. It is then necessary to combine online reviews into a collective preference that summarizes the reviews of all individual users. Some the existing research fuse these online reviews by employing statistics-based information transformation methods (Fan et al., 2018; He & Wang, 2023; Liu & Teng, 2019; Zhang, Zhao, et al., 2020), which process all reviews at the same time, ignoring the opinions of individual users. However, even though reviews belong to the same sentiment level, their sentiment strengths may be different. Besides, each review provided by users should be considered when obtaining collective opinions. To show the superiority of employing the interval MCC model to obtain a collective opinion, we conduct a comparative analysis, which is carried out based on the average of the opinion of each user. The closeness coefficient of alternatives are $CD_1 = [0.383, 0.601]$, $CD_2 = [0.395, 0.604]$, $CD_3 = [0.416, 0.610]$, and $CD_4 = [0.412, 0.616]$. Then, we have $z_4 \succ z_3 \succ z_2 \succ z_1$. Hence, alternative $z_4$ is the best alternative.

From the previous results, we can observe that for the same decision problem with the same information form, the use of the interval MCC model in the process of obtaining collective opinions has a significant impact on the results. This influence is reflected by the uncertainty included in the closeness coefficient and the ranking order. In online reviews, each user contributes their unique experiences, preferences, and perspectives. Consequently, opinions can vary widely among users, with some expressing views that are extremely different from others. However, some of the existing research (Fan et al., 2018; He & Wang, 2023; Liu & Teng, 2019; Zhang, Zhao, et al., 2020) process all online reviews simultaneously and transform them into single values, which may amplify the impact of extreme opinions from individual users, as their views are averaged out as the same way with normal reviews. In contrast, the proposed decision framework obtains collective opinion by interval MCC model, which can ensure that the collective opinion may satisfy all users.

### *6.3. The management of interval uncertainty*

Online reviews are subjectively provided by users, which are often characterized by uncertainty and fuzziness. To effectively capture and represent this uncertainty and fuzziness, some of the existing research transforms them into fuzzy sets, such as intuitionistic fuzzy sets (Li & Zhang, 2021; Liu et al., 2017), probabilistic linguistic term sets (Liang et al., 2021; Liu & Teng, 2019) and picture fuzzy set (He & Wang, 2023). These approaches can preserve the original information contained within online reviews as much as possible. However, the subsequent defuzzification of these proposals often output crisp numbers, potentially leading to information loss.

In contrast, we propose a novel approach to handle the uncertainty and imprecision of hybrid online reviews by transforming them into interval values and conducting decision analysis directly with these intervals, avoiding information defuzzification. In the context of ORDM, interval values are particularly advantageous as they can help to better represent the inherent uncertainty and variability in online review information, which is often characterized by ambiguity, subjectivity, and heterogeneity. To be specific, we define an interval MCC model and an interval TOPSIS method, which can effectively obtain the collective opinion and rank the alternatives. Throughout our study, we do not defuzzify the interval values into crisp numbers, which allows us to retain as much of the original information as possible. Furthermore, this approach extends the applicability of the MCC model and TOPSIS method, allowing for their utilization in an interval value environment.

### 6.4. Management implications

The new ORDM framework proposed aims at offering a systematic approach for utilizing online reviews to assist in decision-making processes. In practice, as long as effective hybrid online reviews can be obtained, the framework can be applied across various domains, such as product development, marketing strategy, and service improvement. Initially, the framework involves the collection of both rating and textual online reviews from relevant platforms, ensuring a comprehensive dataset. Subsequently, the reviews are processed using sentiment analysis techniques to extract valuable insights regarding user opinions and preferences. The integration of hybrid online reviews allows for a holistic understanding of users' opinions, capturing both quantitative ratings and qualitative feedback. Next, an interval MCC model is employed to derive a collective opinion, taking into account the inherent uncertainty and variability present in online reviews. This step ensures that the collective opinion is close to each user's opinion and is more accepted by them. Finally, based on the proposed interval TOPSIS method, interval closeness coefficients are obtained and alternatives are ranked according to these values.

Overall, the proposed ORDM framework facilitates a structured and data-driven approach to decision-making, empowering businesses and organizations to leverage the wealth of information available in online reviews effectively. This framework reduces decision costs by tapping into a diverse range of perspectives from a broad base of users rather than inviting a large number of experts. Compared with traditional decision information collection methods, this is more effective as it removes the limitation of space and time, enabling decision-makers to make timely and informed decisions in response to changing market conditions.

## 7. Conclusions and future research

The widespread use of portable devices and information technologies has led to abundant online reviews. These reviews, containing a wealth of information, can greatly assist decision-making. However, existing research has largely overlooked the utilization of hybrid online reviews, which consist of both rating and textual reviews. Neglecting the analysis of hybrid reviews can lead to inaccurate decision-making. To address this gap, this paper has proposed a novel ORDM framework that integrates LSGDM techniques to effectively manage hybrid reviews. Compared to previous research, our framework offers several advantages:

(1) Improving accuracy and stability. By leveraging hybrid online reviews, our framework achieves more accurate and stable decision results. Unlike studies that solely rely on rating or textual reviews, our approach considers all available information. This holistic perspective helps to minimize bias and instability in decision outcomes.
(2) Considering individual satisfaction. The proposed framework ensures that the collective preference reflects the opinions of all individual users through the implementation of a interval MCC model. By incorporating the opinions of all users, including those with minority views, our framework guarantees that the final decision will closely align with the diverse perspectives within the user base. This approach fosters inclusivity and enhances the fairness of the decision-making process.
(3) Handling interval uncertainty. While the inclusion of interval information is common in decision-making literature, many existing approaches often involve uncertainty reduction methods that result in information loss. In contrast, our framework introduces a novel interval MCC model and an interval TOPSIS method that retains the interval uncertainty without transforming it into crisp values. These methods adhere to widely accepted rules for interval values, ensuring the effective management of uncertainty and imprecision in hybrid online reviews. By preserving the interval nature of the data, our framework maintains the integrity of the information and enables a more accurate representation of the inherent uncertainties within the reviews.

For future research directions, we suggest exploring the following aspects to further enhance decision-making using hybrid online reviews and contribute to the development of advanced decision support systems:

(1) Research on a sentiment analysis method. When utilizing online reviews to aid decision-making, sentiment analysis methods play an important role. However, with several alternatives available, selecting the most suitable method is crucial. In our pursuit of preserving the uniqueness of intervals derived from hybrid online reviews, we aim to explore sentiment analysis methods that are applicable across various languages. This will enhance the applicability and effectiveness of our decision-making framework.
(2) Research on determining opinion leaders. When considering online reviews, it is convenient to take into account the reviews coming from social leaders, such as those published by influential users, or those that receive many likes. These opinions often have a different level of influence compared to regular opinions. Identifying and exploring these influential opinions is an interesting direction for future research.

## CRediT authorship contribution statement

**Xiao-Hong Pan:** Funding acquisition, Validation, Investigation, Writing, Revision. **Shi-Fan He:** Conceptualization, Methodology, Investigation, Writing, Revision. **Diego García-Zamora:** Investigation, Writing, Revision, Visualization. **Ying-Ming Wang:** Funding acquisition, Conceptualization, Supervision, Methodology. **Luis Martínez:** Validation, Writing – review & editing , Revision, Visualization.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data availability

Data will be made available on request.

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