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Product Attribute and Heterogeneous Sentiment Analysis-based Evaluation to Support Online Personalized Consumption Decisions

Zaoli Yang, Qin Li, Nazrul Islam, Chunjia Han, Shivam Gupta

***Abstract*—To effectively address challenges that stem from e-commerce, it is crucial to harness diverse review data from e-commerce platforms. These data support consumers in making informed purchase decisions and aid manufacturers in optimizing product attributes. Incorporating sentiment data from heterogeneous reviews across different time periods into a decision-making framework is a pivotal consideration in purchase decisions and product design. The goal of the study is to establish an online product decision support method grounded in consumer irrational behavior and segmented reviews over time. It aims to offer users reliable and consistent outcomes when making personalized purchase decisions. The probabilistic linguistic term set is employed to represent consumer sentiments with varying degrees of granularity across different time periods. Subsequently, stochastic sampling is utilized to simulate the decision-making process of individual consumers. Regret theory is then applied to analyze consumers' irrational psychological behavior. Building upon heterogeneous data gathered from e-commerce platforms, including review ratings, likes, and follow-up reviews, a multiperiod group decision approach based on maximum similarity and review helpfulness is proposed. This decision-making method is advanced through a decomposition-aggregation process, safeguarding against information distortion and ensuring result reliability. This method provides consumers with product selection solutions across the temporal dimension and serves as a theoretical compass for manufacturers and sellers seeking product enhancement and sales optimization.**

***Index Terms*—Online personalized consumption decision, product attribute evaluation, heterogeneous review sentiments, consumer psychological behavior**

I. INTRODUCTION

WITH the advent of Web 2.0/3.0, people are becoming increasingly dependent on the internet. Many online users have published their reviews of products on website platforms such as blogs, forums, social networking sites, and e-commerce websites [1, 2]. Online reviews have a considerable influence on consumer purchase decisions [3-5], and they are beneficial for merchants to evaluate and improve product attributes [6-8]. With the growth of e-commerce platforms such as Amazon, Alibaba, and JD, e-commerce platforms have attracted an increasing number of consumers who have left many product reviews on these platforms, and the number of reviews continues to increase. Consumers adopt their online consumption strategies by reading as many reviews as possible [9], and merchants want to obtain the most benefit from product feedback to guide product innovation [10].

In recent years, a multitude of studies have delved into utilizing online review data to aid consumers in their purchasing decisions. A crucial concept involves converting extensive review data into diverse decision languages, thereby enabling consumers to make more precise and informed purchase choices or product evaluations [11-13]. When aggregating complex decision languages and information matrices, there is a risk of information loss, and inconsistent decision opinions may occur during the decision-making process [14]. The stochastic simulation technique has the capability to generate multiple random samples based on known decision information, thus providing a more precise data foundation. This technique is employed to sample and statistically analyze heterogeneous decision information, resulting in the creation of a superiority-probability-based pairwise comparison matrix (SPM), which furnishes decision-makers with a probabilistic ranking [15]. However, this approach does not encompass certain psychological factors of decision-makers in the information aggregation process and lacks consideration of specific psychological interaction processes.

Moreover, it is worth noting that the dimension of 'time' significantly influences consumer feedback [17]. Reviewers may exhibit varying tendencies in posting reviews during different time periods, and subsequent consumers tend to refer to prior evaluations and ratings of the product. To address this

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issue, Wu et al. [18] considered the impact of time inconsistency in the decision-making process and established a series of time-related data for each option, thus achieving dynamic decision-making. However, this approach often involves an excessive number of time segments, leading to instability in decision results for specific periods. Furthermore, aggregating decision data from diverse time frames to arrive at a consensus within the group poses a challenge in the temporal dimension of decision-making.

Enhancing group consensus is an effective method for assessing the quality of group decisions [19]. Common indicators for measuring the consensus process include distance [20], consistency [21], and similarity [22]. A consensus process based on maximum similarity is adopted here. Additionally, in group decision-making based on online reviews, the public makes decisions based on the helpfulness of certain reviews, but some studies, such as [23] and [24], have not taken this into consideration. In addition to online reviews, e-commerce platforms offer a range of heterogeneous data, such as review ratings, likes, and follow-up reviews, all of which serve as vital indicators of review helpfulness [25].

As such, this study aims to address the following main research questions:

RQ1. How can consumer preference information be fully expressed in decision language without sacrificing authenticity?

RQ2. How can the online product decision-making process incorporate the user's psychological interaction process?

RQ3. How can heterogeneous data be integrated to ensure data credibility and decision quality?

In response to the research questions, this study proposes an online personalized consumption decision-making method based on review sentiments and consumer psychological behavior to provide consumers with consistent and reliable choices. First, we extract users' heterogeneous sentiments and transform them into a probabilistic linguistic term set (PLTS) to process complex decision data. Meanwhile, inspired by [15], the PLTS is processed by random sampling to cover a variety of possible decision information and simulate the decision-making process of individual consumers. Second, we employ regret theory, which was proposed by Loomes and Sugden [16], to conduct a pairwise comparison of decision options and propose a SPM based on regret theory (R-SPM). Additionally, we delve into the psychological behaviors exhibited by consumers when making purchasing decisions and quantify their preference levels for alternative options. Moreover, in this study, we adopt a group decision approach to consolidate product information across different time periods, ultimately providing consumers with a sound decision framework. Finally, we amalgamate heterogeneous data and employ entropy [26] to calculate the review helpfulness, subsequently integrating it into the group decision-making process. This leads to the proposition of a group decision method rooted in maximum similarity and review helpfulness to ascertain weights across different time dimensions.

The remainder of this paper is arranged as follows. Section II reviews probabilistic language term sets and regret theory, group decision-making based on heterogeneous data, and product ranking methods. Section III introduces the process of data acquisition and the methods used in this study, including the PLTS, regret theory, and the process of maximum consensus based on individual consumers' psychological interaction and the helpfulness of online reviews. Section IV takes consumers buying smartphones as an example and provides the decision results. Section V discusses the results. Section VI provides the conclusions and suggestions for future research.

II. Literature Review

A. Probabilistic Linguistic Term Sets and Regret Theory

In real-life decision-making, most decision-makers articulate their preferences for different options using a range of linguistic terms, each holding varying degrees of importance. To facilitate decision-maker expression, Pang et al. proposed the PLTS [27]. A multiattribute decision method based on PLTS was thus developed. Liu et al. [28] introduced the Muirhead mean aggregation operator into the PLTS based on the Archimedean t-conorm and t-norm and linguistic scale functions and developed the probabilistic linguistic Archimedean Muirhead mean operator. Mao et al. [29] applied the PLTS in group decisions to solve fintech problems and defined the possibility measure and range value of the PLTS. Du et al. [30] proposed a multigranularity probabilistic linguistic model, redefining PLTS multiplication and exponentiation and enhancing the universality of probabilistic linguistic models. Based on this, many scholars have developed dynamic decision-making frameworks using probabilistic linguistic models. For example, Zhang et al. [31] presented a dynamic multiattribute decision-making model by combining a PLTS with Bayesian networks to evaluate network public opinion popularity in emergencies. Zhang et al. [32] developed a process-oriented probabilistic linguistic decision model considering that decision-making behavior requires a certain amount of time and then applied this model to emergency plan selection.

Different decision-makers have different psychological behaviors, such as joy, regret, and disgust [33]. Regret theory describes the bounded rationality psychology of decision-makers in uncertain environments [34], which can dynamically represent the preferences of decision-makers for decision options. Numerous studies have introduced the concept of regret theory into the multiattribute decision method to calculate the regret or joy of decision-makers when facing different choices. Zhang et al. [35] proposed a group decision method based on regret theory to solve the pairwise comparison problem and represent multidimensional decision-maker preferences. Tian et al. [36] integrated regret theory into the PLST group decision, describing the consensus process of decision-making. Some scholars have also proposed a probability interval value hesitation fuzzy dominance scoring method based on regret theory and defined a new regret-joy function [37]. Additionally, regret theory is often used to solve portfolio problems. Gong et al. [38] established a multiobjective portfolio model based on regret theory, allowing investors to adjust their investment behavior from the perspective of regret and information preference. In summary, the primary strength of regret theory lies in its capacity to quantify the emotions of regret or satisfaction experienced by decision-makers when accepting or rejecting a particular plan. This process aids decision-makers in making timely adjustments to their behavior, thereby enhancing the overall quality of their decisions.

B. Group Decision-making based on Heterogeneous Data

Group decision-making entails the collective process of arriving at a decision, offering a comprehensive perspective on the varied preferences of individuals and the consensus reached after the decision [39]. In reality, numerous decision-making scenarios necessitate the use of group decision models. With the explosive growth of the internet and social media, a plethora of studies have emerged to extract valuable insights from content generated by online users, thereby amassing a wealth of individual preference data and enabling public involvement in decision-making processes. Wan et al. [40] carried out sentiment analysis of reviews on social media to reflect decision quality and aggregated group preferences using the weighted arithmetic aggregation operator to support objective large-scale group decision-making (LSGDM). Li [41] combined literature and expert opinions to collect multiple criteria, proposed a fuzzy LSGDM judgment decision matrix and finally adjusted the acceptable consistency based on the opinions of the respondents to achieve group consensus. Group decision-making is also a commonly used method to evaluate the group satisfaction of a certain product. For example, Chen et al. [23] and Ji et al. [24] extracted user preferences from online reviews, supplementing their findings with questionnaire data from a diverse user base. They employed a large-scale group decision approach to independently evaluate user satisfaction with high-speed rail and shared accommodations. In fact, preference information from users can be obtained not only from online comments but also from the introduction of additional indicators that represent user preferences, which can make the decision results more persuasive. Yang et al. [42] investigated diverse forms of user rating data, encompassing comprehensive ratings, user profiles, and multiattribute ratings. They employed information aggregation operators to consolidate these data and developed an online multidimensional rating aggregation decision model to address product ranking challenges.

The objective of group decision-making is to reach consensus, and measuring consensus achievement is also one of the key issues studied by numerous scholars. Consensus is usually judged by criteria such as distance, similarity, and consistency [15]. Pérez et al. [43] summarized the situation of measuring the consensus level from different perspectives; the commonly used method is to define a similarity function based on the distance function between preference values. Kamis et al. [44] conducted clustering based on a preference similarity network structure and then calculated the distance between each category to obtain group consensus. Meng et al. [45] established a two-stage consensus adjustment mechanism through a cooperative game approach. Liu et al. [46] also proposed a consensus feedback strategy for opinion adjustment and dynamic trust interaction based on social network methods. Zhang et al. [47] studied the distance metric based on the intuitive multiplication preference relation to realize the group consensus process. Zhong et al. [48] improved the ordinal distance measurement method to reflect the consensus process. Guo et al. [49] measured the gap between individual opinions and group consensus by calculating the uncertainty distance to reach a consensus process.

C. Product Ranking Method-based Consumption Decisions

To assist consumers in selecting well-suited and highly personalized products, numerous studies have developed diverse approaches for product ranking. This process involves data mining and information fusion, prompting extensive research on computing product rankings through amalgamating multiattribute decision-making methods such as the analytic hierarchy process (AHP), the technique for order preference by similarity to ideal solution (TOPSIS), and fuzzy sets [50]. For example, Gupta et al. [51] constructed the integrated fuzzy AHP to evaluate the selection of green suppliers. Dahooie et al. [52] employed sentiment analysis from online reviews and intuitionistic fuzzy sets in a multicriteria decision-making approach to rank mobile phone products. In the case of products listed on e-commerce platforms, an extensive collection of reviews was examined to extract product attributes. Subsequently, sentiment analysis was performed to categorize sentiments into positive, neutral, and negative sentiments, which were then proportionally transformed into various decision language terms, such as intuitionistic fuzzy sets [53], hesitation fuzzy theory [54], and PLTS [55]. Finally, information aggregation operators tailored to different decision languages were employed to consolidate the performance values for each attribute. By using the above methods, a unique product ranking can be obtained. Nevertheless, this ranking result is derived from a 100% probability, implying the absolute superiority of one scheme over another. In practical scenarios, however, a degree of instability is inevitable, particularly when relying on review data. This introduces a level of uncertainty in product ranking based on such reviews. To this end, some scholars have introduced the concept of probability to represent the dominance relation between products, often falling below 100% [15]. Probability ranking reflects the uncertainty of evaluation results, achieves reliability and confidence in the results to a certain degree, and helps ensure that priority attention is given to uncertainty in the decision-making process. Traditional absolute sorting methods probably cannot clearly distinguish the dominance relation between products. Introducing probability values will make it easier for consumers to choose products and achieve a certain level of interpretability of the results.

By reviewing the above literature, it has been observed that current research still exhibits the following deficiencies in providing decision support for product purchases.

First, regarding user review data extraction, previous research has predominantly performed sentiment analysis on reviews, categorizing sentiments into three broad types: positive, negative, and neutral. However, it is noteworthy that each sentiment can be further nuanced and subdivided for a more detailed analysis. Using a singular fuzzy set to represent multiple granularities of sentiment may not ensure that users' review information can be flexibly reflected in decision language. To address this issue, this paper adopts the PLTS to express consumers' positive and negative sentiment preferences at multiple granularities and further augments it through random sampling, thereby providing a more effective simulation of diverse real-life preferences.

Second, regret theory delineates the emotions of regret and joy experienced by decision-makers when confronted with choices. Previous studies have focused primarily on computing the psychological impact of regret under comprehensive decision preference values without simulating the individual user's psychological behaviors and subsequently amalgamating them. As a response, this paper integrates regret theory and stochastic simulation to address a specific user's decision-making process.

Third, regarding group decision-making based on heterogeneous data, some studies have combined online reviews with questionnaire data for group decision-making. However, other heterogeneous data on online platforms, such as review ratings, likes, and follow-up reviews, were often overlooked. The integration of these diverse data types into the group decision-making process remains an unexplored challenge in current research.

Finally, in terms of product ranking outcomes, a majority of studies present results with an absolute dominance relation, lacking interpretability. To address this, this paper embraces the concept outlined in the literature [15], presenting the product ranking results with probability-based dominance. Building on this, decision language is aggregated using regret theory to dissect the psychological behaviors of consumers.

III. METHODOLOGY

A. *Data Collection and Processing*

The research objects of this study were several different brands of mobile phones: HuaweiMate50 (P_1), iPhone14 Pro (P_2), Vivo X90 (P_3), and Xiaomi12s (P_4). We utilized the Bazhuayu Collector[1] to scrape the reviews of these four mobile phones from various stores within JD.com[2], totaling 35,063 entries. Additional fields included the purchaser's information, star ratings, review texts, and the number of likes and follow-up reviews, as illustrated in Fig.1. The primary temporal distribution of reviews for these four mobile phones spanned from P_1: November 2021 to July 2023; P_2: September 2022-July 2023; P_3: September 2022-July 2023; and P_4: July 2022-July 2023. Then, according to December 2022 and March 2023, the reviews of each brand of mobile phone were divided into three time periods: reviews before December 2022 (T_1), reviews from January 2023 to March 2023 (T_2) and reviews from April 2023 to July 2023 (T_3).

Fig.1. Sample product reviews from Jingdong

[1] https://www.bazhuayu.com
[2] https://www.jd.com

1) Identifying product attribute words

a. Data preprocessing

After the reviews were sorted by time, we performed data cleaning. We preprocessed the text according to the following requirements: ①deleting duplicate reviews, ②deleting uninformative reviews and non-Chinese reviews, and ③ removing reviews of less than 5 words. After processing, 28,183 reviews remained. The Jieba package in Python was then used for word segmentation for each review, removing the stops and identifying the part of speech of each word. Considering that some noise words remained in the review text that were irrelevant to the topic, we allowed the removal of some noise words during topic identification.

b. Topic clustering

The Latent Dirichlet Allocation (LDA) model [56], commonly employed in text analysis and topic modeling, serves as a prominent probability model. It is widely utilized for extracting text topics and related keywords. Additionally, it is frequently applied for the extraction of product or service attributes [57, 58]. In this study, the LDA model, an unsupervised machine learning technique, was adopted to obtain product attributes. This model was implemented using the Gensim library in Python 3.8. After calculating cosine similarity, six topics and their corresponding keywords are determined, i.e., appearance (A_1), configuration (A_2), system performance (A_3), price (A_4), customer service (A_5), and brand (A_6). These six theme keywords were then used as product attribute words. In addition, to contain more keywords under each topic, the word segment and marking function in GooSeeker[3] was applied to segment reviews and filter them by part of speech, including nouns, adjectives, verbs, pronouns and adverbs. Before filtering, the software also filtered out some useless words, e.g., non-Chinese words, numbers, single words, and website addresses. The screening process is shown in Fig.2. Finally, all nouns in the reviews were extracted. All nouns were ranked according to their word frequency, and keywords under each topic were further manually supplemented based on the long tail effect of noun distribution. The final product attributes and keywords obtained are shown in TABLE I.

c. Categories of online reviews

After determining the product attribute words and keywords, we filtered the related reviews according to the keyword dictionary and added reviews that were not filtered by manual recognition. Finally, we obtained the set of reviews R_{ik}^j for attribute A_k of each product P_i at each time T_j.

B. *Sentiment Analysis*

1) Calculating the sentiment score

This subsection involves a sentiment analysis of each review within the review set R_{ik}^j. We employed the SnowNLP package in Python 3.8 to compute the sentiment score for each review. SnowNLP is a robust Chinese text processing library with its own corpus derived from e-commerce website reviews, which proved invaluable for product review sentiment analysis in this study. Additionally, it offers a Bayesian estimation for sentiment analysis, enabling the calculation of sentiment scores for individual review terms within the range of [0,1]. A higher

[3] https://www.gooseeker.com/

score indicates greater emotional intensity in the review, as illustrated in TABLE II.

Fig.2. The process for filtering noise words and parts of speech screening

TABLE I
ATTRIBUTE KEYWORD DICTIONARY

Attributes	Keywords
外观 (A_1) (appearance)	外观、外形、颜色、颜值、曲面、色彩、外观设计、配色、边框、后盖、曲屏、手感、包装、昆仑
配置 (A_2) (configuration)	屏幕、音效、电池、音质、相机、摄像头、照片、耳机、镜头、声音、电量、夜景、画质、重量、扬声器、画面、蓝牙、网络
系统性能 (A_3) (system performance)	运行速度、待机时间、系统、性能、功能、内存、待机、处理器、信号、安卓、鸿蒙、芯片、反应速度
价格 (A_4) (price)	价格、赠品、性价比、礼物、价位
客户服务 (A_5) (customer service)	物流、客服、服务态度、商家、卖家态度、店家
品牌 (A_6) (brand)	华为、苹果、vivo、小米

TABLE II
EXAMPLES OF SENTIMENT ANALYSIS

Review text	Sentiment score
待机时间：待机时间感觉有点短，电池有一些不经用。	0.074
外观真的惊艳了！	0.975
拍的照片清晰。	0.719

2) Sentiment classification and data conversion

Hogenboom et al. [59] argued that sentiment encompasses not only positive and negative aspects but also features a multidimensional hierarchy. Therefore, in this study, we categorized sentiments into multiple levels based on their sentiment scores. Liu et al. [60] divided the sentiment range of [-1, 1] into five levels, establishing a five-granularity PLTS. Following their approach, we refined this by partitioning the sentiment score [0, 1] into two intervals: [0, 0.5) and [0.5, 1]. Subsequently, we further subdivided the sentiment scores within these intervals into finer granularities. As a result, we constructed two five-granularity PLTSs for the sentiment scores within each interval. Consequently, the corresponding probabilistic linguistic term sets under [0.5, 1] and [0, 0.5) are both five-granularity linguistic term sets, designated $E_P=\{e_\delta \mid e_0,e_1,e_2,e_3,e_4\}$ and $E_N=\{e_\varepsilon \mid e_0,e_1,e_2,e_3,e_4\}$, respectively. The semantics conveyed by e_0-e_4, along with their corresponding sentiment score intervals, are detailed in TABLE III.

TABLE III
SENTIMENT CLASSIFICATION RULES AND THEIR CORRESPONDING PROBABILISTIC LINGUISTIC SEMANTICS

E_P			E_N		
LTS	Semantic	Ss	LTS	Semantic	Ss
e_0	Much less positive	[0.5,0.6)	e_0	Much more negative	[0,0.1)
e_1	Less positive	[0.6,0.7)	e_1	More negative	[0.1,0.2)
e_2	Positive	[0.7,0.8)	e_2	Negative	[0.2,0.3)
e_3	More positive	[0.8,0.9)	e_3	Less negative	[0.3,0.4)
e_4	Much more positive	[0.9,1]	e_4	Much less negative	[0.4,0.5)

Note: LTS denotes Linguistic term set, Ss denotes Sentiment score.

Following sentiment classification, it is imperative to map reviews to the respective PLTS. Let $G=\{g_1,g_2,\ldots,g_n\}$ represent a decision information set and $E=\{e_\alpha \mid \alpha=0,1,\ldots,\tau\}$ (where τ is a positive integer) be a set of linguistic terms. We filter each review in R_{ik}^j according to the sentiment score intervals, and at time T_j, the proportion of the number of reviews for product P_i under attribute A_k within each sentiment score interval to the total number of reviews is used as the probability in the PLTS.

The decision information for the sentiment scores of R_{ik}^j that fall in the ranges [0.5, 1] and [0, 0.5) are $M_{ik}^{jP}(p)(g_i)=\left\{e_{\delta^{i(r)}}(p^{(r)}) \mid e_{\delta^{i(r)}}\in E_P, p^{(r)}=\frac{H_{ik}^{jr}}{H_{ik}^{jP}}, r=0,1,\ldots,4\right\}$ and $N_{ik}^{jN}(p)(g_i)=\left\{e_{\varepsilon^{i(t)}}(p^{(t)}) \mid e_{\varepsilon^{i(t)}}\in E_N, p^{(t)}=\frac{H_{ik}^{jt}}{H_{ik}^{jN}}, t=0,1,\ldots,4\right\}$, respectively. Where H_{ik}^{jr} represents the number of reviews classified as $e_{\delta^{i(r)}}$ in reviews, and H_{ik}^{jP} represents the total number of reviews with a sentiment score ranging from [0.5,1]. H_{ik}^{jt} represents the number of reviews classified as $e_{\varepsilon^{i(t)}}$ in reviews, and H_{ik}^{jN} represents the total number of reviews with a sentiment score ranging from [0,0.5]. Then, the complete decision information of R_{ik}^j can be denoted as $R_{ik}^j(p)=\left\{\left\langle g_i, M_{ik}^j(p)(g_i), N_{ik}^j(p)(g_i)\right\rangle \mid g_i\in G\right\}$.

C. Comparison of the Superiority-Probability based on Individual Consumer Psychological Interactions

1) Probabilistic linguistic term sets

Definition 1[27]. Let $E=\{e_\alpha \mid \alpha=0,1,\ldots,\tau\}$ be a linguistic term set (LTS). Then, the PLTS is defined as

$$R(p)=\left\{R^{(r)}(p^{(r)})\mid R^{(r)}\in E, p^{(r)}\geq 0, r=1,2,...,\#R(p), \sum_{r=1}^{\#R(p)} p^{(r)}\leq 1\right\},$$

where $R^{(r)}(p^{(r)})$ is the linguistic term $R^{(r)}$ associated with the probability $p^{(r)}$, and $\#R(p)$ is the number of all different linguistic terms in $R(p)$. If $\sum_{r=1}^{\#R(p)} p^{(r)}=1$, $R(p)$ has complete information on the probabilistic distribution of all possible linguistic terms; if $\sum_{r=1}^{\#R(p)} p^{(r)}<1$, then partial ignorance exists because the current knowledge is not sufficient to provide complete assessment information. In particular, $\sum_{r=1}^{\#R(p)} p^{(r)}=0$ is completely ignored.

2) The calculation process of regret theory under the environment of q-rung orthopair fuzzy sets

When aiding consumers in making purchasing decisions, we define the set of available smartphone products as $P=\{P_1,P_2,...,P_i\}(1\leq i\leq m)$, the set of smartphone attributes as $A=\{A_1,A_2,...,A_k\}(1\leq k\leq n)$, and the set of time periods as $T=\{T_1,T_2,...,T_j\}(1\leq j\leq l)$. Loomes and Sugden [16] introduced regret theory, which aimed to elucidate the irrational psychological tendencies of decision-makers. These individuals possess a specific frame of reference in their decision-making process, which serves as a yardstick for assessing gains and losses following a decision. In essence, when decision-makers opt for one alternative and compare it with others, they experience contentment if the comparative outcome is superior and regret if it falls short. Building on the work of Peng et al. [61], we further extend regret theory to q-rung orthopair fuzzy sets. The detailed computational steps are outlined as follows.

Step 1. Convert the q-rung orthopair fuzzy numbers to interval fuzzy numbers. After obtaining the decision matrices in the form of a PLTS for different time periods, we need to conduct random sampling to simulate the decision-making process of individual consumers. Then, we acquire a q-rung orthopair fuzzy number $w_{ik}^{j}=(\mu_{ik}^{j},v_{ik}^{j})$ by conducting a random sampling of the PLTS. Subsequently, it becomes necessary to transform this q-rung orthopair fuzzy number into an interval number $[W_{ik}^{j^-},W_{ik}^{j^+}]$ using Formulas (1) and (2).

$$W_{ik}^{j^-}=\mu_{ik}^{j} \tag{1}$$

$$W_{ik}^{j^+}=\left(1-(v_{ik}^{j})^{q}\right)^{(\frac{1}{q})} \tag{2}$$

Step 2. Calculate the utility value of attribute A_k according to Formula (3):

$$U_{ik}^{j}=\int_{W_{ik}^{j^-}}^{W_{ik}^{j^+}} u_{ik}^{j}(w)\, f_{ik}^{j}(w)\, dw \tag{3}$$

where $u_{ik}^{j}(w)$ is the utility function and

$$u_{ik}^{j}(w)=\begin{cases}\dfrac{1-e^{-\alpha w}}{\alpha}, 0<\alpha<1\\ \dfrac{1-e^{\beta w}}{\beta}, 0<\beta<1\end{cases} \tag{4}$$

In cases where attribute A_k signifies a beneficial aspect, the upper formula of (4) is employed for computation. Conversely, when attribute A_k denotes a cost factor, the lower formula of (4) is utilized. Both α and β denote decision-maker risk aversion coefficients; their impacts on utility functions pertaining to benefit and cost attributes are illustrated in Fig.3. As depicted in Fig.3, the higher the values of α and β are, the more pronounced the risk aversion tendencies exhibited by decision-makers. $f_{ik}^{j}(w)$ is the probability density function, and w follows the standard normal distribution; that is, $f_{ik}^{j}(w)=\frac{1}{\sqrt{2\pi}\sigma}e^{-\frac{(w-\mu)^2}{2\sigma^2}}$. According to the 3σ principle of probability statistics, the probability that w belongs to the interval $[W_{ik}^{j^-},W_{ik}^{j^+}]$ is 99.73%; that is, $\mu=\left(W_{ik}^{j^-}+W_{ik}^{j^+}\right)/2$ and $\sigma=\left(W_{ik}^{j^+}-W_{ik}^{j^-}\right)/6$.

Step 3. Compute the regret value R_{ibk}^{j} and joy value G_{ibk}^{j} of scheme P_i relative to scheme P_b under attribute A_k.

$$R_{ibk}^{j}=\begin{cases}1-\exp(-\lambda(U_{ik}^{j}-U_{bk}^{j})), & U_{ik}^{j}<U_{bk}^{j}\\ 0, & U_{ik}^{j}\geq U_{bk}^{j}\end{cases} \tag{5}$$

$$G_{ibk}^{j}=\begin{cases}0, & U_{ik}^{j}<U_{bk}^{j}\\ 1-\exp(-\lambda(U_{ik}^{j}-U_{bk}^{j})), & U_{ik}^{j}\geq U_{bk}^{j}\end{cases} \tag{6}$$

In Formulas (5) and (6), λ represents the regret avoidance coefficient. The higher the value of λ is, the more pronounced the degree of regret avoidance exhibited by decision-makers.

Step 4. Normalize the regret-joy value of the above step according to Formulas (7) and (8):

$$\overline{R_{ibk}^{j}}=\frac{R_{ibk}^{j}}{RG_k^{+}} \tag{7}$$

$$\overline{G_{ibk}^{j}}=\frac{G_{ibk}^{j}}{RG_k^{+}} \tag{8}$$

where $RG_k{}^{+}=\max\left\{\max_{i,b=1,2,...,m}\{|R_{ibk}|\}, \max_{i,b=1,2,...,m}\{|G_{ibk}|\}\right\}$, m represents the number of attributes.

Step 5. Count the comprehensive regret value and joy value of scheme P_i relative to scheme P_b according to Formulas (9) and (10):

$$R(P_i^{j})=\sum_{b=1}^{m}\sum_{k=1}^{n}\omega_k\overline{R_{ibk}^{j}}, (i=1,2,...,m) \tag{9}$$

$$G(P_i^{j})=\sum_{b=1}^{m}\sum_{k=1}^{n}\omega_k\overline{G_{ibk}^{j}}, (i=1,2,...,m) \tag{10}$$

Step 6. Obtain the decision-maker's comprehensive utility perception value by Formula (11) and rank the schemes by the value $Q(P_i^j)$.

$$Q(P_i^j) = R(P_i^j) + G(P_i^j), (i = 1, 2, ..., m) \tag{11}$$

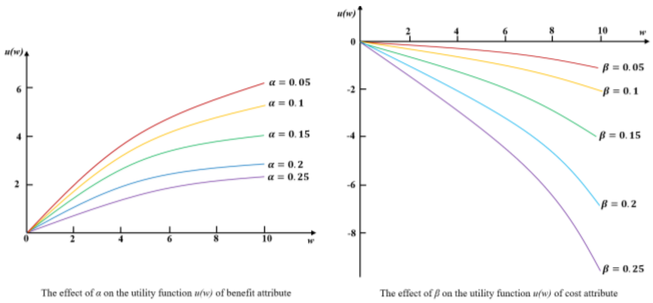

Fig.3. Effects of α and β on the utility function $u(w)$

3) Comparison of the Superiority-probability based on consumer psychological interaction behavior

To accommodate a wider range of sentimental types, we adopted a PLTS to store decision-making information. A PLTS group represents the comprehensive sentiment values of multiple users, which cannot reflect the preference of a single user toward product attributes. To emulate the decision-making psychology and preferences of individual users in real-life scenarios, random PLTS values are generated by drawing inspiration from the random sampling of heterogeneous data in the literature [15]. Following a pairwise comparison of the comprehensive utility values of m products, a single R-SPM is established. The key steps involved are as follows: extracting random PLTS values for each time period, aggregating these values postsampling using regret theory to encapsulate consumers' irrational psychology when evaluating decision options, and finally, comparing the comprehensive performance values of each simulated product in pairs to construct an R-SPM for each time period. Assume that $\{P_1, P_2, ..., P_m\}$ is a set of m products, $\{A_1, A_2, ..., A_n\}$ is a set of n attributes, $\{T_1, T_2, ..., T_l\}$ is a set of l time periods, $R_{ik}^j(p) = \left\{ \left\langle g_i, M_{ik}^j(p)(g_i), N_{ik}^j(p)(g_i) \right\rangle | g_i \in G \right\}$ is the initial decision value, and $w_{ik}^j = (\mu_{ik}^j, v_{ik}^j)$ is the decision value after sampling $R_{ik}^j(p)$, where $i \in \{1, 2, ..., m\}, k \in \{1, 2, ..., n\}, j \in \{1, 2, ..., l\}$.

The steps to build a single R-SPM are as follows:

Step 1. After sentiment analysis and data conversion, the initial PLTS $R_{ik}^j(p) = \left\{ \left\langle g_i, M_{ik}^j(p)(g_i), N_{ik}^j(p)(g_i) \right\rangle | g_i \in G \right\}$ is obtained, and the membership degree and nonmembership degree in the PLTS are converted into corresponding triangular fuzzy numbers $R_{ik}^j(p) = \left\{ \left\langle g_i, MT_{ik}^j(a,b,c), NT_{ik}^j(a,b,c) \right\rangle | g_i \in G \right\}$, which are then randomly sampled h times. The corresponding q-rung orthopair fuzzy sets $w_{ik}^j = (\mu_{ik}^j, v_{ik}^j)$ of Group h are obtained.

Step 2. According to the regret theory calculation process in the part *2)* of Section III.*C*, the attribute values $w_{ik}^j = (\mu_{ik}^j, v_{ik}^j)$ after each sampling are aggregated to describe the decision-making process based on irrational psychological behavior, and the comprehensive utility value $\left\{ z_{1h}^j, z_{2h}^j, ..., z_{mh}^j \right\}$ of m products with each random sampling value in each time period is obtained.

Step 3. After pairwise comparison of the comprehensive utility values $\left\{ z_{1h}^j, z_{2h}^j, ..., z_{mh}^j \right\}$ of h group products in time period T_j, the initial R-SPM is obtained. The process is as follows:

(1) An initial m*m-dimensional pairwise comparison matrix $c^0 = [c_{ik}^0]_{m \times m}$ with each element taking *0*, another m*m-dimensional pairwise comparison matrix $c^{\sim 0} = [c_{ik}^{\sim 0}]_{m \times m}$ with each element taking *0* and the initial R-SPM $RS^0 = [rs_{ik}^0]_{m \times m}$ based on regret theory with all elements *0* are generated.

(2) Let m schemes be pairwise compared with each other; if $z_{ih}^j > z_{kh}^j (i, k = 1, 2, ..., m)$, then $c_{ik}^h = c_{ik}^{h-1} + 1$; if $z_{ih}^j = z_{kh}^j (i, k = 1, 2, ..., m)$, then $\overset{\sim h}{c_{ik}} = \overset{\sim h-1}{c_{ik}} + 1$.

(3) Calculate a single R-SPM, $rs_{ik}^h = (c_{ik}^h + 0.5\overset{\sim h}{c_{ik}}) / h$. rs_{ik}^h is used to represent the probability that product P_i outperforms the other alternatives.

Step 4. The stability of R-SPM is determined. If the distance between elements rs^h and rs^{h-1} is less than a predefined threshold, it is considered stable; then, rs^h can be used as the final R-SPM. Otherwise, we return to Step 3. The formula for calculating the distance between two elements is $\sqrt{\frac{1}{m^2} \sum_{i=1}^m \sum_{k=1}^m \left(rs_{ik}^h - rs_{ik}^{h-1} \right)^2} \le \zeta$, where ζ is a predefined threshold value.

D. Purchase Group Decision-making Based on Maximum Similarity-review Helpfulness

Vital product reviews offer fresh perspectives and insights, bolstering the objectivity and authenticity of group decision-making outcomes. Maximum similarity is a widely utilized metric for gauging consensus in the decision-making process. Building on Li et al.'s work [15], the consensus-building process of maximum similarity was employed, strategically assigning weights to maximize alignment between individual preferences and collective opinions. Expanding on this foundation, heterogeneous data such as review ratings, likes, and number of follow-up reviews were integrated into the group decision-making process. This led to the proposal of a group decision-making approach rooted in both maximum similarity and review helpfulness, enhancing the consensus-building process. The comprehensive weights for a single R-SPM in each time period were derived through the integration of review helpfulness and maximum similarity.

1) Consensus process based on maximum similarity

The similarity-based consensus degree (SCD) is defined according to Formula (12), which is measured by the average distance between a single R-SPM and the collective R-SPM.

$$SCD = \frac{1}{1+\frac{1}{l}\sum_{j=1}^{l} d(rs^*, rs_{T_j})} \tag{12}$$

where $d(rs^*, rs_{T_j}) = \frac{1}{m^2}\sum_{i=1}^{m}\sum_{k=1}^{m}\left(rs_{ik}^* - rs_{ik}^{T_j}\right)^2$ and rs^* is the comprehensive R-SPM. Specifically, the ideal value of the SCD is 1 when different decision schemes in multiple time periods reach a consensus. Based on this, the programming model can be constructed, and the consensus weight $\Gamma^{scd}(T_j)$ based on the maximum similarity can be obtained according to Formula (13):

$$\begin{aligned} &Max\ \mathbf{SCD} = 1/(1+\frac{1}{lm^2}\sum_{j=1}^{l}\sum_{i=1}^{m}\sum_{k=1}^{m}(rs_{ik}^* - rs_{ik}^{T_j})^2) \\ &subject\ to \begin{cases} 0 \le \Gamma^{scd}(T_j) \le 1 \\ \sum_{j=1}^{l}\Gamma^{scd}(T_j) = 1 \\ rs^* = \sum_{j=1}^{l}\Gamma^{scd}(T_j) rs_{ik}^{T_j} \end{cases} \end{aligned} \tag{13}$$

2) Helpfulness score of online reviews

Numerous studies have employed entropy as a yardstick for evaluating the value of a review. Singh et al. [26] established a correlation between entropy and review helpfulness. Fresneda et al. [62] reported a positive impact on review helpfulness. In this study, we also delve into rating stars, likes, and follow-up reviews. Notably, we directly convert the rating stars to their corresponding numerical values; for instance, '5 stars' equates to '5'. To assess the utility of these three forms of data for reviews, we compute the entropy $En(R_i^j)$ for each review across these three types of data, signifying the entropy of product P_i for each review at each time T_j. The formula for calculating entropy is given in Formula (14).

$$H(X \mid Y) = \sum_{i,j} p(x_i, y_i) \log \frac{p(y_j)}{p(x_i, y_j)} \tag{14}$$

Assume that the number of each review of product P_i at each time T_j is η, and the overall review helpfulness at each time T_j is

$$\Gamma^{he}(T_j) = \frac{1}{m}\sum_{i=1}^{m}\left(\frac{1}{\eta}\sum_{R=1}^{\eta} En(R_i^j)\right) \tag{15}$$

3) The overall weight at time T_j

The overall weight at time T_j is given by

$$\Omega(T_j) = \chi\Gamma^{scd}(T_j) + (1-\chi)\Gamma^{he}(T_j) \tag{16}$$

where $\chi \in [0,1]$ is an adjustable parameter used to adjust the specific gravity of two different weights [63].

4) Calculating overall R-SPM

The overall R-SPM is calculated according to Equation (17), and the probability-based product ranking result is obtained.

$$rs^* = \sum_{j=1}^{l} \Omega(T_j) * rs_{T_j} \tag{17}$$

After obtaining the overall R-SPM, we find the ranking results that occur with a certain probability according to the following rule:

Count the number of times the product outperforms the other alternatives and with a probability not less than 0.5, i.e., $f_i = count(rs_{ik} > 0.5) + 0.5count(rs_{ik} = 0.5), k = 1,2,...,n, i \ne k$.

When f_i is larger, then the probability that scheme P_i is better than the other schemes is larger.

We apply the probability value of R-SPM to represent the preference relation between products. If $rs_{ik} > 0.5$, then $P_i > P_k$; if $rs_{ik} = 0.5$, then $P_i = P_k$; if $rs_{ik} < 0.5$, then $P_k > P_i$. The final ordering of the products is $P_i \succ^{rs_{ik}} P_k$.

In summary, the process of making product purchase decisions, rooted in the individual psychological interaction of consumers and the helpfulness of online reviews, unfolds as follows:

Stage 1: Data collection and preprocessing, followed by sentiment analysis, after which the sentiment values are converted into the PLTS.

Stage 2: Random sampling of the PLTS for executing probabilistic superiority comparisons grounded in consumer psychological interaction behavior.

Stage 3: Reaching a group decision founded on the maximum similarity-helpfulness of the review.

The comprehensive decision-making flowchart is illustrated in Fig.4.

IV. Decision-making Process

Stage I.

The decision objects of this study are HuaweiMate50, iPhone14 Pro, Vivo X90, and Xiaomi12s. Then, the product set is $P = \{P_1, P_2, P_3, P_4\}$, and the attributes obtained through the LDA topic model are appearance, configuration, system performance, price, customer service and brand. Then, the attribute set is $A = \{A_1, A_2, A_3, A_4, A_5, A_6\}$. The reviews are classified according to three time periods, and the time set is $T = \{T_1, T_2, T_3\}$. After the sentiment analysis and data transformation of the review set R_{ik}^j in the Section III.C, we obtain the decision matrix in the form of the PLTS under different time periods. Due to a lack of space, we only list the initial decision matrix under T_1, as shown in TABLE IV in the Appendix.

Stage II.

Next, the R-SPM is created following the steps outlined in the Section III.C.

Step 1. The PLTS is initially subjected to random sampling. Prior to this, we transformed it into a triangular fuzzy number [64], as illustrated in TABLE V in the Appendix.

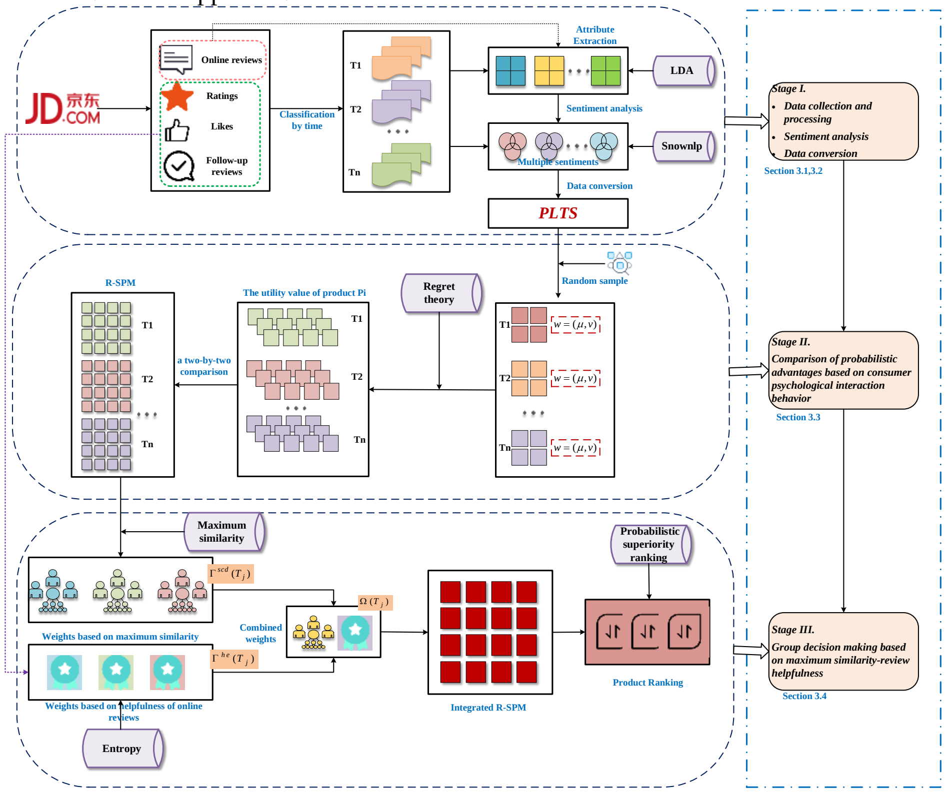

Fig.4. Product purchase group decision-making based on individual consumers' psychological interaction and the helpfulness of online reviews

Subsequently, 10 rounds of sampling are performed to yield 10 sets of q-ROFS random values $w_{ik}^{j}=(\mu_{ik}^{j},v_{ik}^{j})$ for each time period T_i.

Step 2. Regret theory is employed to aggregate the attribute values $w_{ik}^{j}=(\mu_{ik}^{j},v_{ik}^{j})$ after each sampling, describing the decision-making process influenced by irrational psychological behavior. This process yields the comprehensive utility value $\{z_{1h}^{j},z_{2h}^{j},...,z_{mh}^{j}\}$ for m products with random sampling values at each time period. Following the steps outlined for calculating regret theory in Section III.C, the comprehensive utility values for each product after the final 10 sampling iterations are presented in TABLE VI in the Appendix. In this context, each attribute weight is denoted as (0.2,0.1,0.15,0.3,0.1,0.15), q=7, $\alpha=\beta=0.05$, $\lambda=0.3$.

Step 3. The comprehensive utility values $\left\{z_{1h}^{j},z_{2h}^{j},...,z_{mh}^{j}\right\}$ for h groups of products during time period T_j are compared pairwise, leading to the derivation of the initial R-SPM. We set $\zeta=0.05$; then, the R-SPM under three time periods is as follows.

$$rs_{T_1}=\begin{bmatrix}0.5&0.5&0.6&0.4\\0.5&0.5&0.7&0.4\\0.4&0.3&0.5&0.2\\0.6&0.6&0.8&0.5\end{bmatrix},\quad rs_{T_2}=\begin{bmatrix}0.5&0.5&0.4&0.6\\0.5&0.5&0.3&0.6\\0.6&0.7&0.5&0.8\\0.4&0.4&0.2&0.5\end{bmatrix},$$

$$rs_{T_3}=\begin{bmatrix}0.5&0.4&0.3&0.4\\0.6&0.5&0.4&0.4\\0.7&0.6&0.5&0.5\\0.6&0.6&0.5&0.5\end{bmatrix}.$$

We find that each R-SPM $\sqrt{\frac{1}{m^2}\sum_{i=1}^{m}\sum_{k=1}^{m}\left(rs_{ik}^{h}-rs_{ik}^{h-1}\right)^2}$ is less than 0.05 and can proceed to the next stage.

Stage III. According to the Section III.C, we aggregate the R-SPM under the three time periods for the group consensus process.

a. Calculate the weight of each time period based on the maximum similarity.

$\Gamma^{scd}(T_j)=(0.333,0.333,0.333)$.

b. Compute the weight of each time period based on the helpfulness of online reviews.

$\Gamma^{he}(T_j)=(0.330,\ 0.344,\ 0.326)$.

c. Count the overall weight at time T_j, where $\chi=0.5$ and $\Omega(T_j)=\chi\Gamma^{scd}(T_j)+(1-\chi)\Gamma^{he}(T_j)$.

$\Omega(T_j)$ =(0.332,0.339,0.330).

d. Calculate the collective R-SPM and obtain the probabilistic advantage of the product as follows:

$$rs^* = \begin{bmatrix} 0.5 & 0.467 & 0.433 & 0.468 \\ 0.533 & 0.5 & 0.466 & 0.468 \\ 0.567 & 0.534 & 0.5 & 0.502 \\ 0.532 & 0.532 & 0.498 & 0.5 \end{bmatrix}$$

After obtaining the comprehensive R-SPM, based on $f_i = count(rs_{ik} > 0.5) + 0.5count(rs_{ik} = 0.5)$ ($k = 1, 2, ..., n, i \neq k$), we can determine that the final probability ranking result for the products is $P_3 \overset{0.502}{\succ} P_4 \overset{0.532}{\succ} P_2 \overset{0.533}{\succ} P_1$.

V. Discussion

A. Results Analysis

Based on the conclusive findings, P_3 (VivoX90) emerges as the optimal selection, boasting a 50.2% likelihood of surpassing P_4 (Xiaomi12s), a 53.4% chance of outperforming P_2 (iPhone14Pro), and a 56.7% probability of surpassing P_1 (Huawei Mate 50). On the basis of randomly sampling the preference information of 10 consumers, a consistency ranking is obtained for three different time periods after considering the irrational psychology of each consumer and the helpfulness of the reviews. Fig.5 displays the utility values of various products derived from four sets of simulated values across different attributes at T_1. Each product exhibits distinct utility values across various attributes, indicating that users undergo unique psychological reactions and experience states of regret and joy when presented with diverse decision options. Consequently, in consumer product decisions, it is crucial to consider these irrational psychological factors. Figs. 6 and 7 reveal dynamic shifts in product rankings over time, leading to different probability rankings generated by the R-SPM matrix for each time period. This observation aligns with scenarios where the sequential order of individually calculated dominance probabilities differed at each time.

Therefore, we obtain

$$rs_{T_1} = \begin{bmatrix} 0.5 & 0.5 & 0.6 & 0.4 \\ 0.5 & 0.5 & 0.7 & 0.4 \\ 0.4 & 0.3 & 0.5 & 0.2 \\ 0.6 & 0.6 & 0.8 & 0.5 \end{bmatrix}, \quad rs_{T_2} = \begin{bmatrix} 0.5 & 0.5 & 0.4 & 0.6 \\ 0.5 & 0.5 & 0.3 & 0.6 \\ 0.6 & 0.7 & 0.5 & 0.8 \\ 0.4 & 0.4 & 0.2 & 0.5 \end{bmatrix},$$

$$rs_{T_3} = \begin{bmatrix} 0.5 & 0.4 & 0.3 & 0.4 \\ 0.6 & 0.5 & 0.4 & 0.4 \\ 0.7 & 0.6 & 0.5 & 0.5 \\ 0.6 & 0.6 & 0.5 & 0.5 \end{bmatrix}.$$

As a result, the ranking under T_1 is $P_4 \overset{0.6}{\succ} P_1 \overset{0.5}{=} P_2 \overset{0.7}{\succ} P_3$, the ranking under T_2 is $P_3 \overset{0.6}{\succ} P_1 \overset{0.5}{=} P_2 \overset{0.6}{\succ} P_4$, and the ranking under T_3 is $P_3 \overset{0.5}{=} P_4 \overset{0.6}{\succ} P_2 \overset{0.6}{\succ} P_1$. During various time periods, consumers encounter distinct situational factors, leading to varied product preferences. We observe that until T_1 (before December 2022), Xiaomi12s (P_4) held the top position. However, in 2023, Vivo X90 (P_3) emerged as a favored choice among consumers. This underscores the importance of considering the time factor in our study. We organized the earlier data by time segments, offering decision results specific to each period. This serves as a valuable resource for both consumers and businesses, aiding them in selecting and enhancing products based on the preferences of different time frames.

B. Parameter Analysis

In this section, we observe variations in the ranking results by altering the weights of the product attributes, as demonstrated in TABLE VII and Fig.8. Through parameter analysis, it becomes evident that as consumers assign varying weights to product attributes, product rankings and their corresponding dominance probabilities undergo significant shifts. When the attribute weights are set to (0.5, 0.1, 0.1, 0.1, 0.1, 0.1), indicating a greater emphasis on appearance attributes, the probability ranking of the four products is $P_4 \overset{0.533}{\succ} P_3 \overset{0.533}{\succ} P_2 \overset{0.6}{\succ} P_1$, making Xiaomi12s the optimal choice.

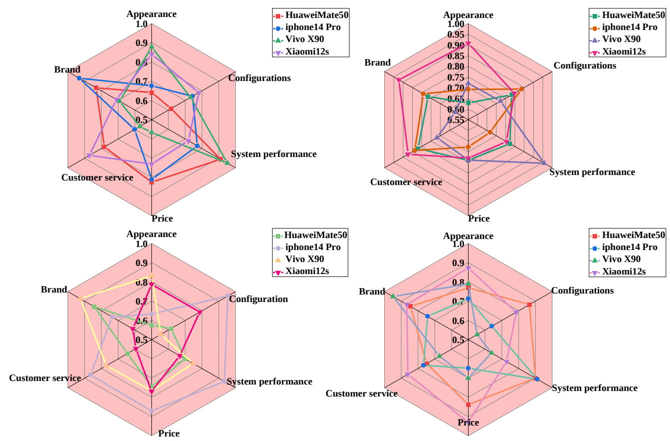

Fig.5. Product performance values represented by four sets of random values at T_1

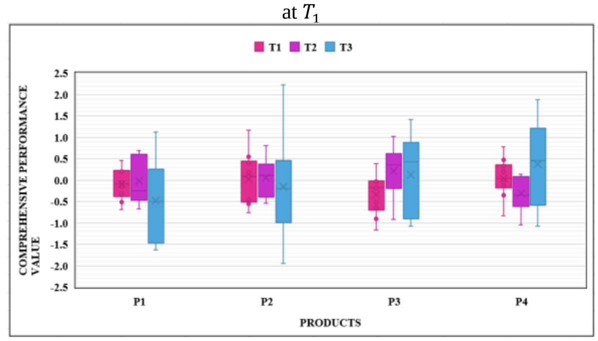

Fig.6. Boxplots of the comprehensive performance values of different products for each time period

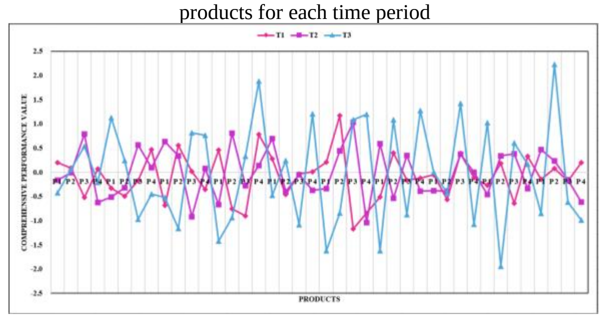

Fig.7. Ranking results of the different products in each time period (10 random values)

This implies that Xiaomi12s is 53.3% more likely to outperform Vivo X90, 59.9% more likely to outperform iPhone 14 Pro, and 70% more likely to outperform Huawei Mate 50. When the attribute weights are adjusted to (0.1, 0.1, 0.5, 0.1, 0.1, 0.1), highlighting the importance of system performance, the product probability ranking shifts to $P_3 \overset{0.533}{\succ} P_2 \overset{0.632}{\succ} P_1 \overset{0.5}{=} P_4$, with Vivo X90 emerging as the preferred option. Vivo X90 exhibits a 56.6% likelihood of surpassing Huawei Mate 50, a 53.3% probability of outperforming iPhone 14 Pro, and a 56.7% chance of exceeding Xiaomi12s. In the scenario where the attribute combination is (0.1, 0.1, 0.1, 0.5, 0.1, 0.1), signifying a greater consideration of price, the product ranking is $P_3 \overset{0.533}{=} P_1 \overset{0.567}{\succ} P_2 \overset{0.501}{=} P_4$. Notably, Vivo X90 and Huawei Mate 50 share the same ranking and outperform iPhone 14 Pro and Xiaomi12s. With attribute weights set at (0.1, 0.1, 0.1, 0.1, 0.1, 0.5), consumers prioritizing brand influence in their smartphone selection, resulting in a product ranking of $P_2 \overset{0.5}{\succ} P_3 \overset{0.533}{\succ} P_1 \overset{0.501}{=} P_4$, making iPhone 14 Pro the optimal choice. This finding also highlights that Vivo X90 is dominant in terms of system performance and price; Xiaomi12s excels in appearance, while iPhone 14 Pro exerts greater influence through brand effects.

In addition, adjusting the weights of attributes can help pinpoint the specific areas that require improvement for each product, thereby offering theoretical support for product innovation among manufacturers. In conclusion, through statistical analysis of the bottom three ranked decision results for each group, this study presents a summary of the attributes that warrant enhancement for each mobile phone model, as detailed in TABLE VIII. The attributes that need to be improved by Huawei Mate50 are appearance, system performance, price, and brand. For iPhone 14 Pro, the areas for improvement include appearance, system performance, and price. For Vivo X20, the attributes that require enhancement are appearance and brand. Xiaomi12s, on the other hand, needs improvements in system performance, price, and brand.

Therefore, consumers can assign different weights to their preferred attributes so that they can obtain different solutions. Additionally, mobile phone manufacturers can further improve mobile phones according to consumers' attribute preferences.

TABLE VII
PRODUCT PROBABILITY RANKING UNDER DIFFERENT WEIGHTS

ω	Comprehensive R-SPM	Probability ranking
(0.5,0.1,0.1, 0.1,0.1,0.1)	$\begin{bmatrix} 0.5 & 0.4 & 0.467 & 0.3 \\ 0.6 & 0.5 & 0.467 & 0.401 \\ 0.533 & 0.533 & 0.5 & 0.467 \\ 0.7 & 0.599 & 0.533 & 0.5 \end{bmatrix}$	$P_4 \overset{0.533}{\succ} P_3 \overset{0.533}{\succ} P_2 \overset{0.6}{\succ} P_1$
(0.1,0.1,0.5, 0.1,0.1,0.1)	$\begin{bmatrix} 0.5 & 0.368 & 0.434 & 0.5 \\ 0.632 & 0.5 & 0.467 & 0633 \\ 0.566 & 0.533 & 0.5 & 0.567 \\ 0.5 & 0.367 & 0.433 & 0.5 \end{bmatrix}$	$P_3 \overset{0.533}{\succ} P_2 \overset{0.632}{\succ} P_1 \overset{0.5}{=} P_4$
(0.1,0.1,0.1, 0.5,0.1,0.1)	$\begin{bmatrix} 0.5 & 0.567 & 0.467 & 0.535 \\ 0.433 & 0.5 & 0.432 & 0.501 \\ 0.533 & 0.568 & 0.5 & 0.468 \\ 0.465 & 0.499 & 0.532 & 0.5 \end{bmatrix}$	$P_3 \overset{0.533}{=} P_1 \overset{0.567}{\succ} P_2 \overset{0.501}{=} P_4$
(0.1,0.1,0.1, 0.1,0.1,0.5)	$\begin{bmatrix} 0.5 & 0.468 & 0.467 & 0.501 \\ 0.532 & 0.5 & 0.5 & 0.568 \\ 0.533 & 0.5 & 0.5 & 0.468 \\ 0.499 & 0.432 & 0.532 & 0.5 \end{bmatrix}$	$P_2 \overset{0.5}{\succ} P_3 \overset{0.533}{\succ} P_1 \overset{0.501}{=} P_4$

C. Contributions

Based on the results analysis and parameter analysis, this study primarily focuses on the following aspects.

(1) An R-SPM is proposed to describe consumers' psychological decision behaviors. By introducing regret theory, pair comparisons are conducted between schemes to simulate the psychological interaction process of consumers. The analysis of this section reveals the impact of consumers' psychological behavior when comparing options on decision-making outcomes.

(2) The temporal dimension is incorporated by categorizing reviews into distinct time periods and computing the product decision matrix for each interval. This approach grants consumers valuable insights into the evolving dynamics of product advantages over time. Following this, the decision matrices undergo aggregation through group decision-making, ensuring that consumers receive dependable and uniform product selection strategies.

(3) After parameter analysis, the optimal decision-making scheme changes, and attribute weights influence the decision results. By adjusting the weights, we can pinpoint the advantageous attributes of each product as well as areas for improvement. This process provides theoretical support for manufacturers seeking to enhance their products.

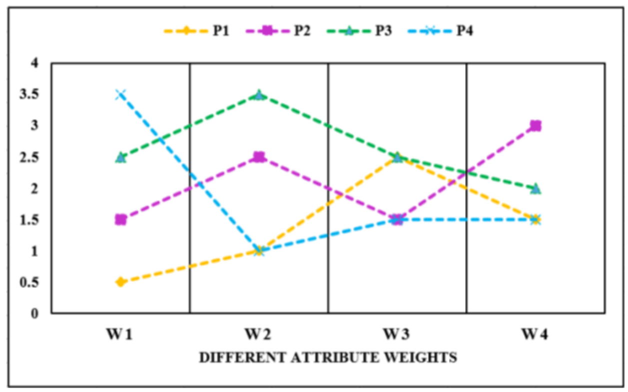

Fig.8. Ranking results of the products with different weights

TABLE VIII
ATTRIBUTES THAT NEED TO BE UPGRADED IN ALL FOUR PRODUCTS

Products	Attributes
HuaweiMate50	Appearance, system performance, price, brand
iPhone14 Pro	Appearance, system performance, price
Vivo X20	Appearance, brand
Xiaomi12s	System performance, price, brand

VI. Conclusion

Using four mobile phones as a case study, we extract online reviews from three distinct time periods. These data serve to offer consumers reliable and consistent decision-making frameworks for smartphone purchases through group consensus. The primary significance of this study is outlined below.

(1) Unlike prior studies, this paper incorporates the time element, resulting in product ranking outcomes for distinct time intervals. These three sets of results are subsequently amalgamated to formulate a balanced recommendation. This process of decision decomposition and aggregation offers consumers and manufacturers valuable insights for product selection and enhancement within the temporal dimension. Additionally, it equips sellers with strategic information for sales efforts and provides a basis for analyzing variations in product sales.

(2) In this study, the PLTS is used to represent positive and negative sentiments at various granularities, enhancing the range of expression for user emotional preferences. Different from previous studies, the comprehensive sentiment values under each attribute are used to make decisions for consumers and then randomly sampled to simulate the decision-making process of a specific consumer. After random sampling, regret theory is used for aggregation, thus incorporating consumer psychological behavior into the decision-making framework and making the decision more logical and realistic.

(3) This study incorporates heterogeneous data, including review helpfulness indicators such as review ratings, likes, and follow-up reviews, into the group consensus process. A group decision method based on maximum similarity and review helpfulness is introduced. Unlike traditional single evaluation index models, this approach ensures a more comprehensive reflection of product quality and consumer experiences. By integrating multiple indices, product quality can be thoroughly evaluated from various perspectives, providing consumers with a more extensive information set. Furthermore, integrating these indices into the group consensus process enhances data credibility and accuracy, providing consumers with a more reliable foundation for making purchasing decisions.

This study has certain limitations. First, the random sampling frequency is restricted, and in the future, increasing the sampling frequency can enable a more accurate simulation of the decision-making processes of a larger consumer base. Second, as mentioned in this study, decision schemes exhibit variability over time, underscoring the significance of time as a factor influencing decision outcomes. However, the study does not delve further into explaining how time precisely impacts decision outcomes or the specific factors leading to varying product ranking results at different times. This field offers potential for causal analysis in future research. Finally, the measurement of review helpfulness relies solely on three indices (review ratings, likes, and follow-up reviews). In reality, numerous other indices are available for assessing review helpfulness. Future research can incorporate the textual content and sentiment within reviews into the review helpfulness measurement model, thereby yielding more dependable decision-making results.

APPENDIX

TABLE IV

INITIAL DECISION MATRIX (T_1)

T_1	A_1	A_2
P_1	$\langle\{s_0(0.01),s_1(0.01),s_2(0.02),s_3(0.03),s_4(0.94)\},\{s_0(0.30),s_1(0.20),s_2(0.10),s_3(0.13),s_4(0.27)\}\rangle$	$\langle\{s_0(0.02),s_1(0.04),s_2(0.07),s_3(0.11),s_4(0.76)\},\{s_0(0.34),s_1(0.16),s_2(0.15),s_3(0.17),s_4(0.17)\}\rangle$
P_2	$\langle\{s_1(0.02),s_2(0.02),s_3(0.05),s_4(0.91)\},\{s_0(0.48),s_1(0.10),s_3(0.19),s_4(0.24)\}\rangle$	$\langle\{s_0(0.03),s_1(0.01),s_2(0.02),s_3(0.07),s_4(0.87)\},\{s_0(0.30),s_1(0.26),s_2(0.22),s_3(0.09),s_4(0.13)\}\rangle$
P_3	$\langle\{s_0(0.01),s_1(0.01),s_2(0.02),s_3(0.04),s_4(0.93)\},\{s_0(0.43),s_1(0.29),s_2(0.07),s_3(0.07),s_4(0.14)\}\rangle$	$\langle\{s_0(0.02),s_1(0.04),s_2(0.05),s_3(0.08),s_4(0.81)\},\{s_0(0.28),s_1(0.16),s_2(0.19),s_3(0.22),s_4(0.16)\}\rangle$
P_4	$\langle\{s_1(0.01),s_2(0.02),s_3(0.04),s_4(0.92)\},\{s_0(0.45),s_1(0.19),s_2(0.06),s_3(0.17),s_4(0.13)\}\rangle$	$\langle\{s_0(0.01),s_1(0.06),s_2(0.08),s_3(0.12),s_4(0.73)\},\{s_0(0.36),s_1(0.12),s_2(0.18),s_3(0.13),s_4(0.20)\}\rangle$
	A_3	A_4
P_1	$\langle\{s_0(0.04),s_1(0.05),s_2(0.06),s_3(0.11),s_4(0.74)\},\{s_0(0.15),s_1(0.17),s_2(0.15),s_3(0.25),s_4(0.29)\}\rangle$	$\langle\{s_0(0.04),s_1(0.03),s_2(0.07),s_3(0.13),s_4(0.74)\},\{s_0(0.52),s_1(0.15),s_2(0.11),s_3(0.07),s_4(0.15)\}\rangle$
P_2	$\langle\{s_0(0.01),s_1(0.05),s_2(0.04),s_3(0.08),s_4(0.81)\},\{s_0(0.34),s_1(0.13),s_2(0.13),s_3(0.16),s_4(0.25)\}\rangle$	$\langle\{s_0(0.02),s_1(0.06),s_2(0.02),s_3(0.04),s_4(0.86)\},\{s_0(0.25),s_2(0.5),s_4(0.15)\}\rangle$
P_3	$\langle\{s_0(0.02),s_1(0.05),s_2(0.06),s_3(0.08),s_4(0.79)\},\{s_0(0.31),s_1(0.08),s_2(0.08),s_3(0.31),s_4(0.23)\}\rangle$	$\langle\{s_2(0.09),s_3(0.03),s_4(0.88)\},\{s_0(0.29),s_2(0.43),s_4(0.29)\}\rangle$
P_4	$\langle\{s_0(0.03),s_1(0.05),s_2(0.05),s_3(0.09),s_4(0.78)\},\{s_0(0.28),s_1(0.21),s_2(0.15),s_3(0.14),s_4(0.21)\}\rangle$	$\langle\{s_0(0.01),s_1(0.03),s_2(0.05),s_3(0.06),s_4(0.85)\},\{s_0(0.47),s_1(0.12),s_2(0.12),s_3(0.18),s_4(0.12)\}\rangle$
	A_5	A_6
P_1	$\langle\{s_0(0.05),s_1(0.04),s_2(0.07),s_3(0.13),s_4(0.71)\},\{s_0(0.41),s_1(0.16),s_2(0.10),s_3(0.16),s_4(0.16)\}\rangle$	$\langle\{s_0(0.03),s_1(0.05),s_2(0.09),s_3(0.10),s_4(0.73)\},\{s_0(0.27),s_1(0.20),s_2(0.12),s_3(0.11),s_4(0.31)\}\rangle$
P_2	$\langle\{s_0(0.04),s_1(0.06),s_2(0.04),s_3(0.14),s_4(0.72)\},\{s_0(0.54),s_1(0.11),s_2(0.09),s_3(0.09),s_4(0.17)\}\rangle$	$\langle\{s_0(0.43),s_1(0.07),s_2(0.07),s_3(0.07),s_4(0.36)\},\{s_0(0.01),s_1(0.02),s_2(0.01),s_3(0.08),s_4(0.88)\}\rangle$
P_3	$\langle\{s_0(0.02),s_1(0.04),s_2(0.05),s_3(0.16),s_4(0.72)\},\{s_0(0.29),s_1(0.43),s_2(0.14),s_4(0.14)\}\rangle$	$\langle\{s_0(0.06),s_1(0.09),s_2(0.05),s_3(0.06),s_4(0.74)\},\{s_0(0.08),s_1(0.31),s_2(0.15),s_3(0.23),s_4(0.23)\}\rangle$
P_4	$\langle\{s_0(0.05),s_1(0.05),s_2(0.05),s_3(0.11),s_4(0.73)\},\{s_0(0.48),s_1(0.09),s_2(0.21),s_3(0.16),s_4(0.06)\}\rangle$	$\langle\{s_0(0.05),s_1(0.05),s_2(0.05),s_3(0.11),s_4(0.73)\},\{s_0(0.49),s_1(0.09),s_2(0.21),s_3(0.14),s_4(0.07)\}\rangle$

TABLE V

PLTS CONVERTED TO TRIANGULAR FUZZY NUMBERS

		A_1	A_2	A_3	A_4	A_5	A_6
T_1	P_1	<(0,0.97,1), (0, 0.47,1)>	<(0,0.89,1), (0,0.42,1)>	<(0,0.87,1), (0,0.59,1)>	<(0,0.87,1), (0,0.30,1)>	<(0,0.85,1), (0,0.38, 1)>	<(0,0.86,1), (0,0.49,1)>
	P_2	<(0,0.96,1), (0,0.4,1)>	<(0,0.94,1), (0,0.37,1)>	<(0,0.91,1), (0,0.46,1)>	<(0,0.92,1), (0,0.5,1)>	<(0,0.86,1), (0,0.31,1)>	<(0,0.95,1), (0,0.46, 1)>
	P_3	<(0,0.97,1), (0,0.3,1)>	<(0,0.9,1),(0,0.45,1)>	<(0,0.89,1), (0,0.52,1)>	<(0,0.95,1), (0,0.5,1)>	<(0,0.88,1), (0,0.32,1)>	<(0,0.83,1), (0,0.56,1)>
	P_4	<(0,0.97,1), (0,0.34,1)>	<(0,0.87,1), (0,0.42,1)>	<(0,0.89,1), (0,0.45,1)>	<(0,0.92,1), (0,0.5,1)>	<(0,0.88,1), (0,0.32,1)>	<(0,0.83,1), (0,0.56,1)>
T_2	P_1	<(0,0.98,1), (0,0.27,1)>	<(0,0.93,1), (0,0.44,1)>	<(0,0.91,1), (0,0.56,1)>	<(0,0.96,1), (0,0.33,1)>	<(0,0.68,1), (0,0.37, 1)>	<(0,0.93,1), (0,0.32, 1)>
	P_2	<(0,0.95,1), (0,0.36,1)>	<(0,0.89,1), (0,0.39,1)>	<(0,0.83,1), (0,0.45,1)>	<(0,0.92,1), (0,0.33,1)>	<(0,0.89,1), (0,0.30, 1)>	<(0,0.93,1), (0,0.43,1)>
	P_3	<(0,0.96,1), (0,0.52,1)>	<(0,0.9,1),(0,0.37,1)>	<(0,0.9,1), (0,0.49,)>1	<(0,0.92,1), (0,0.32,1)>	<(0,0.82,1), (0,0.34,1)>	<(0,0.87,1), (0,0.53, 1)>
	P_4	<(0,0.97,1), (0,0.38,1)>	<(0,0.91,1), (0,0.29,1)>	<(0,0.9,1), (0,0.48,1)>	<(0,0.96,1), (0,0.45,1)>	<(0,0.86,1), (0,0.37, 1)>	<(0,0.94,1), (0,0.37,1)>
T_3	P_1	<(0,0.97,1), (0,0.3,1)>	<(0,0.91,1), (0,0.3,1)>	<(0,0.89,1), (0,0.46,1)>	<(0,0.94,1), (0,0.17,1)>	<(0,0.92,1), (0,0.24, 1)>	<0,0.95 ,1), (0,0.31, 1)>
	P_2	<(0,0.95,1), (0,0.35,1)>	<(0,0.91,1), (0,0.39,1)>	<(0,0.88,1), (0,0.56,1)>	<(0,0.9,1),(0,0.45,1)>	<(0,0.92,1), (0,0.24, 1)>	<(0,0.95,1), (0,0.31, 1)
	P_3	<(0,0.96,1), (0,0.49,1)>	<(0,0.91,1), (0,0.46,1)>	<(0,0.9,1), (0,0.56,1)>	<(0,0.94,1), (0,0.41,1)>	<(0,0.88,1), (0,0.38, 1)>	<(0,0.88,1), (0,0.48,1)>
	P_4	<(0,0.95,1), (0,0.22,1)>	<(0,0.9,1),(0,0.23,1)>	<(0,0.9,1), (0,0.3,1)>	<(0,0.95,1), (0,0.21,1)>	<(0,0.9,1), (0,0.13,1)>	<(0,0.93,1), (0,0.17, 1)>

TABLE VI
COMPREHENSIVE UTILITY VALUES OF EACH PRODUCT AT DIFFERENT TIMES

		T_1	T_2	T_3			T_1	T_2	T_3
1	P_1	0.200	-0.161	-0.425	6	P_1	0.206	-0.338	-1.625
	P_2	0.091	-0.005	0.060		P_2	1.169	0.438	-0.841
	P_3	-0.516	0.787	0.539		P_3	-1.167	1.030	1.081
	P_4	0.073	-0.620	-0.211		P_4	-0.838	-1.045	1.201
2	P_1	-0.330	-0.512	1.124	7	P_1	-0.512	0.587	-1.623
	P_2	-0.491	-0.322	0.241		P_2	0.400	-0.539	1.085
	P_3	-0.174	0.567	-0.967		P_3	-0.169	0.343	-0.879
	P_4	0.471	0.097	-0.449		P_4	-0.120	-0.389	1.271
3	P_1	-0.688	0.635	-0.516	8	P_1	-0.051	-0.378	0.002
	P_2	0.551	0.342	-1.163		P_2	-0.563	-0.387	-0.435
	P_3	0.021	-0.922	0.812		P_3	0.393	0.369	1.423
	P_4	-0.359	0.080	0.765		P_4	-0.113	0.004	-1.072
4	P_1	0.458	-0.669	-1.418	9	P_1	-0.269	-0.456	1.020
	P_2	-0.758	0.803	-0.938		P_2	0.182	0.340	-1.942
	P_3	-0.900	-0.281	0.329		P_3	-0.637	0.378	0.607
	P_4	0.781	0.140	1.882		P_4	0.326	-0.340	0.161
5	P_1	0.275	0.697	-0.481	10	P_1	-0.143	0.470	-0.847
	P_2	-0.458	-0.399	0.245		P_2	0.079	0.237	2.231
	P_3	-0.034	-0.050	-1.080		P_3	-0.183	-0.160	-0.615
	P_4	0.007	-0.377	1.204		P_4	0.201	-0.615	-0.984

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