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Research on the Evolution of Consumers' Purchase Intention Based on Online Reviews and Opinion Dynamics

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Abstract: Due to the development of the e-commerce platform and the internet technology, the inclination of consumers for online shopping is shooting up. To lure consumers and gratify consumers, it's necessary for enterprise to explore and excavate the purchase intention evolution mechanism so that enterprises can customize the marketing strategies and get consumers to purchase products. Previous studies have shown that consumers' purchase intention is influenced significantly by online reviews. However, the mechanism by which consumers' real purchase intentions change when they refer to online reviews is unclear. In fact, the process that consumers browse online reviews is truly an opinion interaction process between recipients (consumers who buy goods) and reviewers (consumers who post online reviews). Interaction between opinions may lead to changes in consumers' purchase intentions. Therefore, an opinion dynamics model, the Deffuant–Weisbuch (D-W) model, is introduced and improved to explore the dynamic evolution of consumers' purchase intention. Firstly, online reviews are executed. Then, fuzzy quantification of sentimental opinion values is performed through trapezoidal fuzzy numbers. Secondly, the improved D-W model is constructed considering the influence of the personality of recipients and the professionalism of reviewers on opinion interaction and the "negative bias" mechanism. Finally, a case study is constructed with online reviews of a cell phone by using the above method. In addition, sensitivity analyses are conducted for the personality coefficient of recipients, professionalism of reviewers, and size of heterogeneous consumers, respectively, through which, the validity of the proposed method is expounded. This study not only contributes to an in-depth discussion about the influencing factors of purchase intention, but also provides references for enterprises to better utilize online reviews to promote products and attract consumers.

Keywords: purchase intention; online reviews; Deffuant–Weisbuch model; sentiment analysis; fuzzy mathematics; dynamic behavior

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1. Introduction

With the rapid development of e-commerce platforms and the accelerated pace of consumer life, online shopping has become one of the mainstream ways for consumers to purchase products and services [1]. A large number of online reviews of online shopping have been presented. Online reviews include much useful information about the experiences of a product or service submitted by consumers [2,3], which is an important way for consumers to obtain cognitive value [4]. Consumers often refer to online reviews before making a purchase decision [5,6]. They can constantly receive the benefits and disadvantages of the product or services [7] and gradually update their purchase intentions dynamically [8,9]. Moreover, the change in consumers' purchase intention signifies the change of consumer opinions. Grewal et al. [10] believe that consumers can further generate purchase intentions only after they have other value cognition. Therefore, consumers' purchase intentions could be greatly affected by online reviews, and it's necessary to study how the purchase intentions of consumers change dynamically under the influence of online reviews. The change of consumers' purchase intentions can reflect the potential demand for a product [11]. Studying the change in purchase intentions is particularly critical for enterprises to lure and gratify consumers and to provide references for enterprises to better utilize online reviews to promote products and attract consumers.

Previous research has shown that the change in the purchase intention of consumers is mainly affected by online reviews during online shopping. The research usually focuses on the content features and quality features of online reviews. The former mainly includes the length [12,13], number of online reviews [14], emotional polarity [15–17], etc. The latter mainly includes integrity [18], timeliness [19], the involvement of online reviews [20], etc. Rare studies have attempted to analyze the evolution process of consumer purchase intention based on online reviews. Chen et al. [21] modified the receipt-accept-sample (RAS) model to analyze the change process of consumer purchase intention when they received positive and negative opinions, respectively. However, there are still some blanks in the modeling of the change in purchase intention considering the influencing relationship between consumers and online reviews.

In practice, the process that consumers browse online reviews is truly the interaction of opinions between the recipients (consumers who browse reviews) and the reviewers (consumers who post online reviews). In this study, an improved Deffuant–Weisbuch (D-W) model is proposed to describe and analysis the opinion interaction process. For one thing, recipients of different personalities can interact with review opinions expressed by reviewers with different levels of professionality. The degree of opinion acceptance between recipients and reviewers is influenced by the combination of recipient personalities and reviewer professionality. On the other hand, practically, consumers usually focus more on negative reviews. Thus, the "negative bias" mechanism is taken into account in the D-W model. Generally, the online review is a format of emotional expression [22], and it is ambiguous. The trapezoidal fuzzy number is introduced to quantify the opinions implied in online reviews, which is more consistent with the fuzziness of online reviews.

This paper is organized as follows. Section 2 reviews the previous findings about consumer purchase intention influenced by online reviews and the dynamic change of consumers' purchase intention. Section 3 outlines the handling of fuzzy quantification of online reviews and model construction of purchase intention evolution. In Section 4, a case study is presented, including the research analysis and findings. Section 5 presents conclusions, limitations, and future works.

2. Related Works

The purchase intention of consumers is a prerequisite for the occurrence of purchase behavior. It contributes to defining marketing objectives for enterprises to study the influence factors of consumer purchase intention. The factors influencing consumers' purchase intention have been paid more attention to study. For example, Liu et al. [23] found that the corporate social responsibility of companies effectively promotes the purchase intention of consumers. Zhuang et al. [24] divided the influence factors for the green purchase intention of consumers into three categories: cognitive, consumer individual, and social factors. By using the meta-analysis, the authors found that collectivism and green perceived risk have the most positive and negative impact on the green purchase intention of consumers, respectively. Zhang et al. [25] showed that website design, information quality, and service quality have a direct significant impact on purchase intention. Wang et al. [26] thought that trust positively influences the purchase intention of consumers on shopping websites.

As numerous online reviews are derived from shopping websites, which have gradually influenced the purchase intention of consumers. At present, a number of scholars have studied the influencing factors of online reviews on consumers' purchase intention, including content features and quality features of online reviews. As to the content features, Ketron et al. [12] and Zhong et al. [13] found that the review length has a significant influence in consumers' purchase intention and positively affects purchase decision significantly. Cain et al. [14] demonstrated that positive framing, abstract numerical presentation, and a small number of reviews result in more favorable evaluations and intentions than negative framing, concrete presentation, and a large number of reviews. Consumer intention to purchase can be influenced by the emotional polarity of online reviews [15]. Su et al. [16] and Yan et al. [17] both thought that positive reviews and negative reviews are different influences for purchase intention and the positive reviews are more significant to consumers' intention to purchase. Chang et al. [27] found that humorous and funny language is more likely to stimulate consumers to feel positive about the advertising stimulus, which in turn leads to a higher willingness to buy. Park et al. [28] found that extreme ratings of online reviews (positive or negative) are more useful and enjoyable than moderate ratings. Kang et al. [29] used the two-stage least squares method to analyze the influence of various factors on consumers' purchasing decisions and found that consumers do not follow the positive guidance and make purchase decisions as we would expect when confronted with a large number of positive emotional polarity online reviews. It may have something to do with consumers traits. As to the quality characteristic of online reviews, Cox et al. [18] indicated that consumers' reactions to textual errors are moderated by their general trust in others. Hwang et al. [19] revealed that the completeness, flexibility, and timeliness of the argument quality positively influence user satisfaction. Park et al. [20] demonstrated that the quality of online reviews has a positive effect on consumers' purchasing intention, and low-involvement consumers are affected by the quantity rather than the quality of reviews, but high-involvement consumers are affected by review quantity mainly when the review quality is high. Wang et al. [30] proposed a moderated moderation model and present that sponsorship disclosure of positive reviews negatively influences consumers' purchase intention and review credibility mediates the relationship. Von et al. [31] found that young people are more inclined to buy products with better attributes and higher ratings than older people. Xiao et al. [32] combined the information adoption model (IAM) and information transmission theory to establish the influence mechanism model of electronic word of mouth(e-WOM) information structures on generation Z consumers' purchase intentions. Xu et al. [33] investigated the effects of conflicting online reviews on purchase intention to find the cognitive dissonance mechanism. The above studies mainly concentrate on statically analyzing consumer purchase intention based on online reviews.

Consumers' purchase intention is also dynamically affected by online reviews. For example, Park et al. [9] applied the elaboration likelihood model and cognitive fit theory to explore how consumers process online reviews depending on the level of their professionalism. Chen et al. [21] proposed an opinion evaluation model based on the receipt-accept-sample (RAS) model to study the dynamic information process of consumers and analyze what is an individual's final attitude when affected by both positive and negative reviews. Zou et al. [34] modified the Deffuant–Weisbuch (D-W) model by introducing negativity bias and review helpfulness to study the dynamic evolution process of online reviews. Jiang et al. [35] combined the Hegselmann–Krause model with the heterogeneity of consumers, merchants' review display methods, and investment behaviors to explore the online opinions in a merchant–consumer interaction process. Although the change process of consumers' purchase intention is theoretically emphasized in these studies, the real evolution process of consumer purchase intention during browsing online reviews has not been sufficiently explored. Therefore, this paper constructs the evolution model of purchase intention to analyze individual and group final purchase intentions when affected by both positive and negative reviews.

Consumers' purchase intentions are changed constantly when they browse online reviews. The process that consumers browse online reviews is an opinion interaction process between the recipients and the reviewers. The D-W model is a classical opinion dynamics model which can describe the interactions between individuals in a population on the opinion evolutionary process. It can provide an opportunity to analyze the evolution process of consumer purchase intention. Considering the interaction mode between recipients and online reviews, the D-W model is improved in the bound of interaction and model of interaction to adapt to the real state. The contribution of this study is twofold as follows.

(1) The fuzzy quantification of online reviews is performed by the trapezoidal fuzzy number. Generally, consumers usually express their opinion in reviews, which are vague. The trapezoidal fuzzy number can be transformed to real numbers and triangular fuzzy numbers, and more consumer real needs can be satisfied.
(2) Opinion similarities between consumer and online reviews and the "negative bias" mechanism are considered in the bound of the improved D-W model. Opinion similarity restricts the degree of the interaction relationship, which can better simulate the state of consumers browsing online reviews. The "negative bias" mechanism can fit the general mentality that customers are always sensitive to negative reviews and will interact with them.

3. Methodology

Now, consumers are frequently exposed to online reviews, including positive, average, or negative information about product. Online reviews act as a communication medium between recipients (potential consumers) and reviewers (purchased consumers), which is an important channel for consumers to obtain product information [1]. Recipients will change their purchase intention by obtaining the positive or negative information. Through mining online reviews, the opinions of reviewers are obtained, and then the evolution model of consumers' purchase intention will be constructed according to the status of consumers browsing online reviews.

As shown in Figure 1, an improved D-W model based on online reviews is built to portray the dynamic evolution process of consumer purchase intention. There are three key parts to be carried out as follows.

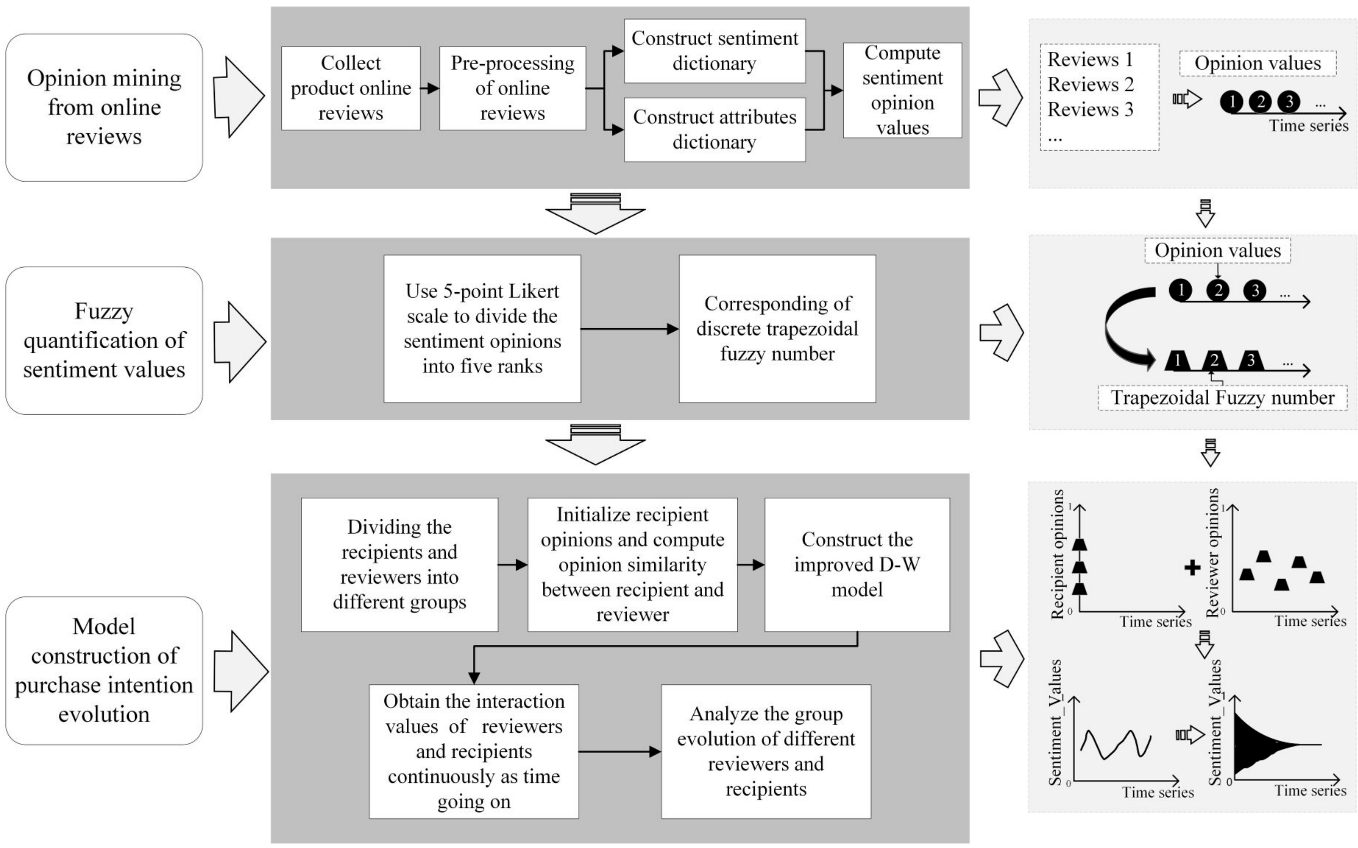


Figure 1. Flowchart of the dynamic evolution model of consumer purchase intention.

1. Opinion mining of online review. A text analysis technique based on the sentiment dictionary is constructed to obtain the opinion values of online reviews.

2. Fuzzy quantification of sentiment values. Online reviews are an expression of ambiguity. The trapezoidal fuzzy number is introduced to quantify online review opinions based on a five-point Likert scale method.
3. Model construction of purchase intention evolution. The recipients and reviewers are divided into different groups. The improved D-W model is constructed to analyze the evolution model of consumer purchase intention.

3.1. Opinion Mining from Online Review

Opinion mining is used to identify opinions from free texts and determine sentiment polarity for a subject or topic [36], also known as sentiment analysis. It can be used to reveal consumer opinions on various product features [37]. In fact, online reviews are a form of product opinions posted by consumers, which hide a large amount of product information [38]. To obtain the opinion values of online reviews, this paper adopts a text analysis technology based on the sentiment dictionary [39]. It mainly involves the following two steps: (1) The initial review dataset is acquired and pre-processed. First, online reviews are obtained by web scraping software. Second, the attribute dictionary is constructed through the LDA topic model and the sentiment dictionary is constructed. Third, the pre-processing of initial online reviews is conducted by removing noises, such as default characters and stop words. Finally, relevant sentiment expressions of consumer emotion about product attributes are extracted from online reviews. (2) Sentiment opinion values are mined. The opinion value of online reviews is computed for every attribute and all attribute opinion values are summed to obtain the overall opinion value.

3.1.1. Acquisition and Pre-Processing of the Initial Review Dataset

Existing studies show that the purchase intention of consumers is affected by online reviews when consumers browse online reviews, that is, consumers interact with ideas from online reviews [15–31]. It is worth noting that consumers are also affected by the identity characteristics of reviewers in the process of interaction [40,41]. Therefore, reviews crawled should contain two parts: review contents and reviewer ranks. This study adopts web crawling software to collect online reviews and reviewer ranks on the e-commerce shopping platform as the initial review dataset.

Next, the initial review dataset is pre-processed to obtain the attribute dictionary and sentiment dictionary which are the basis of emotion analysis. The attribute dictionary can locate the topic of product features more accurately [42]. The sentiment dictionary can identify the sentiment polarity of the text more quickly [43]. The attribute dictionary will be extracted by the LDA topic model. The process of constructing the attribute dictionary is as follows. First, the initial review dataset is segmented and conducted with part-of-speech (POS) tagging of Jieba. Then tagging result of each review is saved to the TXT file by line. The POS of tagging includes nouns, verbs, adjectives, quantifiers, adverbs, adjuncts, conjunctions, and so on. It should be noted that adjunct and conjunction have no practical significance in sentiment analysis and can only add to the complexity of program operation. These useless words are removed from the TXT file by loading the stop word list, which is derived from the aggregation and deduplication of the deactivation word list of the Harbin Institute of Technology, the deactivation word database of the Machine Intelligence Laboratory of Sichuan University, and the deactivation word list of Baidu. Finally, the review segmentation dataset is obtained.

Based on the review segmentation dataset, the LDA model is trained by the term frequency-inverse document frequency (TF-IDF) corpus. By constructing TF-IDF, setting the number of attributes (n-topics) and the number of characters (n-top-words), and performing extraction and classification of product feature words, the topic classification results are obtained after several debugging efforts. The results are processed by manual debugging, and the attribute dictionary is shown in Table 1.

Table 1. The attributes dictionary of the product.

Attribute	Character Word
Attribute A1	$A_{11}, A_{12}, A_{13}, \ldots\ldots$
Attribute A2	$A_{21}, A_{22}, A_{23}, \ldots\ldots$
……	……
Attribute Am	$A_{m1}, A_{m2}, A_{m3}, \ldots\ldots$

Consumer preference for a product is generally expressed in online reviews [36]. To capture the sentiments of consumers towards a product, the sentiment dictionary is needed. The sentiment dictionary is the key to text analysis and is divided into three parts: the emotion dictionary, the negation dictionary, and the degree adverb dictionary. The emotion dictionary is obtained from the integration and de-duplication of the sentiment dictionary of China National Knowledge Infrastructure (CNKI), National Taiwan University, Tsinghua University, and review-related sentiment words. The negation dictionary and the degree adverb dictionary are complied with based on related reviews. Besides, the sentiment dictionary is labeled intensity of review sentiment words to achieve the quantification of sentiment [44]. The form of intensity labeling is (key: value). 'key' stands for the sentiment word (including positive word, negative word, negation word, and degree adverb). 'value' stands for the intensity of the sentiment word. The sentiment dictionary of a product is shown in Table 2.

Table 2. Sentiment dictionary of a product.

Part-of-Speech	Key	Value	Representation
Emotion word	positive negative	1 −1	k_e
Negation word	negation	−1	k_g
Degree adverb	strong medium weak	1 0.5 0.1	k_d

Note: The positive sentiment word is indicated $k_e = 1$; the negative sentiment word is indicated $k_e = -1$. The negation sentiment word is indicated $k_g = -1$. The strong degree adverb is indicated $k_d = 1$; the neutral degree adverb is indicated $k_d = 0.5$; The weak degree adverb is indicated $k_d = 0.1$.

Attribute dictionaries and sentiment dictionaries are obtained after online reviews are preprocessed. The above dictionary can directly locate the key position of the sentiment opinion, and then accurately extract the consumer opinion value.

3.1.2. Computation of the Sentiment Opinion Values

The mining of the sentiment opinion values is based on the sentiment dictionary and attribute dictionary. For every attribute, character words are searched for the initial review dataset to obtain review sentences/phrases with character words. Then, these review sentences/phrases are segmented and labeled the POS by Jieba, before removing noises from the sentences/phrases, such as stop words and useless words. In this way, the character word and its corresponding review sentences/phrases can be identified as the review segmentation sentence. Next, the opinion value of every attribute is mined based on the labeled value of the sentiment dictionary.

Generally, online reviews contain sentiments about the different attributes of a product. The sum of each attribute sentiment makes up the emotion of a review. Therefore, the M attribute opinion values are calculated separately. The sum of M attribute opinion values is deemed as the review sentiment value V. The corresponding equations are shown in Equations (1)–(3).

$$\mathrm{W}_n = k_g^n * k_d^n \tag{1}$$

$$V = \sum_{m=1}^{M} V_m \tag{2}$$

$$V_m = \sum_{n=1}^{N} W_n * k_e^n \tag{3}$$

where V_m indicates the opinion value of product attribute m in the review sentence. V denotes the sum of review sentiment values of the m attributes. W_n denotes the weight of the n-th emotion word, k_e denotes the sentiment value of emotion words, k_d denotes the value of degree adverbs, and k_g denotes the value of negative words.

The process of mining is as follows. First, aiming at the review segmentation sentence of every online review, search for the emotion words, negative words, and degree adverbs in turn. Then, beginning with the first emotion word, the weight W of every emotion word is calculated by the product of the negative words and degree adverbs searched for. The sum of the product of weight W and emotion value k_e is regarded as sentiment opinion values. For example, starting with the first emotion word, the initial weight W_0 is set to 1. The k_d of the degree adverb is multiplied with W_0 to get W_1 if there is a degree adverb in front of the emotion word; the label value k_g is multiplied with W_1 to get W_2 if there is a negation word in front of the emotion word. The k_e of the emotion word is multiplied by W_2 to obtain the sentiment value V_1. Then, the next emotion word is searched for until N emotion words in the sentence are traversed. The sum of sentiment values of N emotion words calculated is the sentiment value of a review about an attribute. In this study, each product attribute and its corresponding sentiment value can be mined by the text sentiment analysis technology above.

3.2. Fuzzy Quantification of Sentiment Values

An online review is usually a fuzzy evaluation to a product [45] and has a subjective preference. The real number can make the evaluation results deviate from consumers' actual opinions if it is used to quantify online reviews [46]. In fuzzy theory, the trapezoidal fuzzy numbers can be interconverted between triangular fuzzy numbers and real numbers. It can match more realistic demands. Therefore, trapezoidal fuzzy numbers are used as the form of online review sentiment values. Combing with a Five-Point Likert scale, the online review opinions are classified into five levels: best, better, average, worse, and worst. Each level is assigned the corresponding trapezoidal fuzzy number to represent consumers' fuzzy sentiment values on whether they like the product or not. The correspondence between sentiment opinion values and the discrete fuzzy number is shown in Table 3.

Table 3. Correspondence between review emotion value and discrete fuzzy number.

Degree of Sentiment	Denotation	Scope of Value	Trapezoidal Fuzzy Number
Best	Strongly positive	$[1, +\infty)$	[0.8, 0.85, 0.95, 1]
Better	Mediumly positive	$[0.5, 1)$	[0.6, 0.65, 0.75, 0.8]
Average	Weakly positive or weakly negative	$(-0.5, 0.5)$	[0.4, 0.45, 0.55, 0.6]
Worse	Mediumly negative	$(-1, -0.5]$	[0.2, 0.25, 0.35, 0.4]
Worst	Strongly negative	$(-\infty, -1]$	[0, 0.05, 0.15, 0.2]

The Schematic diagram of opinion and the choice of discrete fuzzy numbers as shown in Figure 2. Based on the above methods, fuzzy opinion values can be obtained.

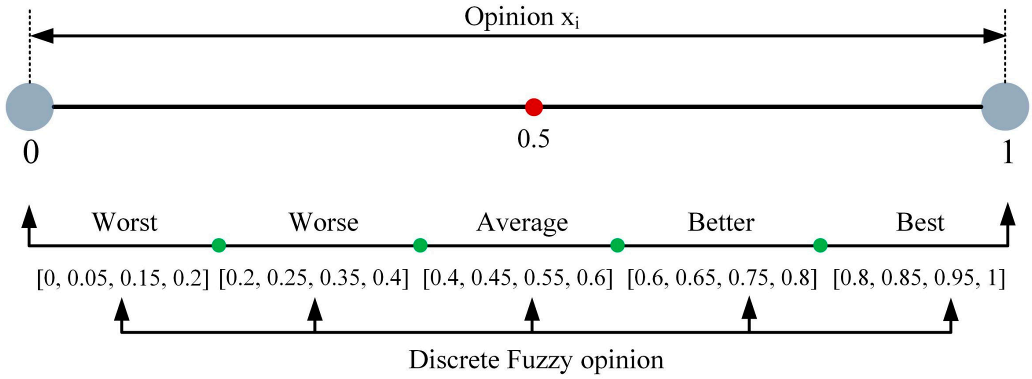


Figure 2. Schematic diagram of opinion and the choice of discrete fuzzy numbers.

3.3. Model Construction of Purchase Intention Evolution

Online reviews are a way for reviewers to share their experiences after purchasing a product. Review recipients can obtain more real product information and experience-based reviews by browsing online reviews so that they can grasp the product better [47]. In fact, recipients are influenced by the opinions of reviewers, and their purchase intentions also continually change in the process of browsing reviews. To investigate the evolution process of purchase intention, the modified D-W model [48] is proposed, the basic idea of which is that individuals can only interact with each other when the difference between their opinions is within a certain threshold. Otherwise, both parties will keep their original opinions. In the process of online shopping, the main body of opinion interaction includes two parts: recipient and reviewer. The classical D-W model only takes into account the trust threshold (recipient personality coefficient) and does not take into account the influence of the reviewer's professionalism. Therefore, the professional coefficient of the reviewer is added in the improved D-W model and jointly affects the opinion interaction with the personality coefficient of the recipient. Moreover, the "negative bias" mechanism is taken into account in the model. Recipients are more likely to pay attention to negative reviews and interact with negative reviews directly without any constraints. This aspect is not considered in the classical D-W model. Another difference from the classical DW model is the expression of confidence threshold. The inter-individual fuzzy similarity S_{ij} [49] are taken into account in the improved model. The recipient's opinion will remain original if the two opinions are extremely dissimilar and they will not trust each other. The recipient will be assimilated by the reviewer's opinion when the two opinions are extremely similar. Based on the above improvements, the improved model satisfies the interaction state of consumers when browsing online reviews.

The opinions of online reviews have positive, average, and negative directions. The degree of consumers to interact is enhanced or weakened depending on whether the opinions received by the recipient are in the same or opposite direction to their own. In the process of opinion interaction, if the opinions between the recipients and reviewers remain in the same direction, the opinions of both sides will be enhanced on the original basis; if the opinions of both sides remain in opposite directions, the opinions of recipients will tend to reviewers and weaken their own opinions. As Figure 3 shows, there are four areas: positive enhancement of the same direction, negative enhancement of the same direction, weakening of the opposite direction, and negative weakening of the negative bias mechanism, which represents the following four situations.

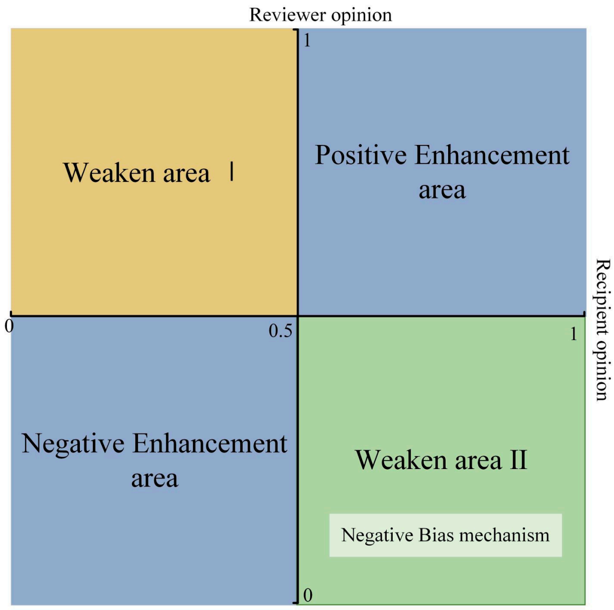


Figure 3. Schematic representation of the classification of interaction areas.

Positive enhancement and negative enhancement of the same direction is the case that recipients and reviewers are the homogeneous opinions. They all reinforce their own emotions in this case. As the review database is composed of N reviews, in which each review is relatively independent and represents a kind of opinion. If the opinion values of recipient i and reviewer j are in the same direction and similar at time t, the opinions of the recipient i tend to be partially or completely aligned with those of the reviewer j. If the recipient's opinion and the reviewer's opinion are in the same direction, but not similar, then the recipient i will maintain his original point. The recipient i updates his opinion x_i^t as the following rules

$$x_i^{t+1} = \begin{cases} x_i^t, & 0 < S_{ij} < \tau \\ x_i^t + cr_i cp_j\left(x_j^t - x_i^t\right), & \tau < S_{ij} < \varepsilon \\ x_j^t, & \varepsilon < S_{ij} < 1 \end{cases} \tag{4}$$

where x_i^t and x_j^t denote the opinion value of consumers i and j at time t, respectively; ε and τ ($\varepsilon,\ \tau \in [0,1]$) are the assimilation threshold and repulsion threshold, respectively, which can reflect the level of interaction in different situations. cr_i , cp_j represent the recipient personality coefficient and reviewer professionalism respectively. S_{ij} denotes the opinion fuzzy similarity degree between i and j, and its calculation rules are shown in Equations (5)–(7).

$$S_{ij} = \left(1 - \frac{\sum_{i=1}^{4}|ai - bi| + \left|x_i^* - x_j^*\right|}{5}\right) \times \frac{\min\left(y_{i,}^* y_{j,}^*\right)}{\max\left(y_{i,}^* y_{j,}^*\right)} \tag{5}$$

$$x_i^* = \frac{y_i^*(a3 + a2) + (a4 + a1)(1 - y_i^*)}{2} \tag{6}$$

$$y_i^* = \frac{\left(\frac{a3 - a2}{a4 - a1} + 2\right)}{6} \tag{7}$$

The homogeneous opinions of recipient i and reviewer j are represented the $(\mathrm{E}(x_i^t) - 0.5) \cdot (\mathrm{E}(x_j^t) - 0.5) > 0$ or $\mathrm{E}(x_i^t) = \mathrm{E}(x_j^t) = 0.5$, where $\mathrm{E}(x)$ denotes the expected value of opinion, and this value is compared with 0.5 to determine the positive and negative opinion. If $\mathrm{E}(x) > 0.5$, then it indicates the positive opinion value; if $\mathrm{E}(x) < 0.5$, it indicates the negative opinion value. The calculation for the opinion of the expected value $\mathrm{E}(x)$ is shown in Equation (8).

$$\mathrm{E}(x_i) = \frac{a2 + a3}{2} + \frac{a4 - a3 + a2 - a1}{6} \tag{8}$$

where x_i, x_j denote the fuzzy number of recipients and reviewers, respectively, $x_i = (a_1, a_2, a_3, a_4)$, $x_j = (b_1, b_2, b_3, b_4)$; (x_i^*, y_i^*) denotes the center of gravity coordinates of the trapezoidal fuzzy number x_i, and (x_j^*, y_j^*) denotes the center of gravity coordinates of the trapezoidal fuzzy number x_j.

However, if a recipient i and a reviewer j is heterogeneous opinions, and the recipient i receives a higher opinion from reviewer j, that is $\mathrm{E}\left(x_i^t\right) < \mathrm{E}(x_j^t)$, as shown in weaken area I of Figure 3. The opinion interaction between the recipient and the reviewer only occurs in the case of a similar opinion and does not occur in the case of extremely dissimilar opinions. Consumers will be less receptive to more positive reviews of products and weaken the initiative. The formula is shown in Equation (9).

$$x_i^{t+1} = \begin{cases} x_i^t + cr_i cp_j \left(x_j^t - x_i^t\right), & \tau \leq S_{ij} \leq 1 \\ x_i^t, & else \end{cases} \tag{9}$$

If the recipient can receive a lower review opinion than their own, that is $\mathrm{E}\left(x_i^t\right) > \mathrm{E}(x_j^t)$, as shown in weaken area II of Figure 3. The recipient will trigger the "negative bias" mechanism in this case. Recipients always pay special attention to negative reviews in online shopping, which depends on the negative bias theory of social behavior. They will trust and interact with the reviewer directly, regardless of the similarity between the recipient and the reviewer. The formula is shown in Equation (10).

$$x_i^{t+1} = x_i^t - cr_i cp_j \left| x_j^t - x_i^t \right| \tag{10}$$

4. Case Study

Nowadays, consumers are increasingly interested in online shopping, and the widespread, large number and accessibility of online reviews make them become an effective way for consumers to obtain product information [50]. Consumers usually refer to online reviews when purchasing products and constantly update their own will to buy. As cell phones have come to occupy daily life, the demand for purchasing cell phones using an e-commerce platform is huge. This paper selects a flagship cell phone of a brand as the research object, which helps enterprises quickly understand the cell phone market, and timely adjust the marketing strategy, which increases the practicability of the article. In addition, online reviews are mined from the JD mall as click farming and false propaganda are not allowed on JD Mall, which also makes the user data of JD closer to the real voice of real users. Therefore, a simulation analysis of how online reviews affect the purchase intention of consumers is conducted according to the research method proposed.

4.1. Acquisition and Processing of Dataset

To simulate the full interaction between vast consumers, a total of 1000 reviews of a brand of a cell phone in JD Mall are crawled by Octopus which are as the initial review dataset. The initial review dataset contains two parts: review contents and reviewer ranks. Then, the preprocessing of initial dataset is performed through word separation and stop word removal. Next, the attribute dictionary is extracted by LDA topic clustering from the review dataset. The final results of attribute dictionary are manually debugged and processed to obtain the attribute dictionary for a cell phone, as shown in Table 4. The sentiment dictionary of a cell phone is referred to in Section 3.1.1 for the positive sentiment dictionary, negative sentiment dictionary, negation dictionary, and degree adverb dictionary, as shown in Table 5 below.

Table 4. Attribute dictionary of a brand of a cell phone.

Attribute	Character Word
Appearance	design, style, facevalue, shape, appearance, color, icon, desktop theme, page, perception, color schemes, size, workmanship, outer frame, back
Screen and Sound	screen, animation, visual effects, clarity, recognition, image resolution, picture quality, filtration, color, timbre, voice, audio effect, music, loudspeaker, stereo, surround sound, sound effect, speaker, telephone, ring
Photo and Camera	photo, lens, front, camera, night view, imaging, video, telephoto, wide-angle lens, picture, colorimetric, telephoto lens, record
Standby Time	endurance, charging, battery capacity, power consumption, capacity, electricity, quantity of electric charge, battery
System operation	operating system, running speed, download speed, speed, power consumption, stuck/frozen, hardware, chip, refresh rate, sensitivity, smoothness, memory capacity, memory, storage, compatibility, game
Service and Experience	earphone, charger, weight, thickness, feel, heat, touch, fingerprint, curved surface, arc, micro-curved, signal, network, network speed, cyber, unlock, lock screen, development, experience, software, control, hand grip, anti-shake, touch screen, face recognition
Others	harmony, kirin, price-quality ratio, price, level, service life, send out, logistics, distribution, packaging, quality, delivery, bonding, payment, release, product, brand, physical, snatch, effect

Table 5. The sentiment dictionary of a cell phone.

Part-of-Speech	Key	Word	Value
Emotion word	positive	benefit, gift, good, great, beautiful, crazy, nameless, amazing, bonus, domineering, applicable, hospitable, reliable, excited, make progress, ultra-portable, love, witty, successful, honest, smooth, quick, improving, etc.	1
	negative	competitive, fragile, invisible, dominant, vulgar, inconsiderate, anxious, third-rate, power consuming, slow, stuttering, stuttering, simple, dusty, rotten, etc.	−1
Negation word	negation	not, not a little, not very, not much, how not, hardly, never, don't use, shouldn't, don't, can't, no, very little, hasn't, isn't, hardly, put down, stifle, terminate	−1
Degree adverb	strong	very, double, extreme, unbearable, sufficient, end, particularly, extremely, absolutely, amazing, etc.	1
	medium	quite, quite a few, not better, surprisingly, much, can, really, etc.	0.5
	weak	more or less, slightly, a little, some, mildly, half	0.1

The mining method of sentiment opinion values is referred to in Section 3.1.2. The fuzzy quantification of opinion value is referred to in Section 3.2. The partial result of quantification is shown in Table 6.

Table 6. The fuzzy quantification of online review.

Online Review	Reviewer Rank	Trapezoidal Fuzzy Number
Appearance: beautiful, pink, feel super good, round running speed: fast, much faster than p40pro, harmony system operates smoothly	PLUS user	[0.4, 0.45, 0.55, 0.6]
Pretty good things. Authentic goods! It works very well. Appearance: Bright Screen sound: Good Photo effect: Great Running speed: always good	PLUS user and evaluation officer	[0.8, 0.85, 0.95,1]

Table 6. *Cont.*

Online Review	Reviewer Rank	Trapezoidal Fuzzy Number
Do not know when and why the mobile phone begins to not match the charger. Does the consumption level of native people has satisfied the mobile phone for single use? The series also does not indicate the case. The customer service persists they are always like this and recommends buying the official standard charger. The order page only has a standard series. How do I know there is no charger? I remember I bought mate40pro with a charger a year ago. Has technology developed so fast? Mobile phones do not have a charger have been the default industry rules? Shouldn't anything that breaks the default rules have a strong text reminder? Playing some word games hurts the hearts of the fans.	Evaluation officer	[0.4, 0.45, 0.55, 0.6]
My husband sent it as a gift during double eleven. The screen is very large and feels just suitable in the hand. Quality of sound is good. Screen resolution is also very good, and there is the eye protection mode. Watching videos is not dazzling. Double eleven is very special.	Ordinary	[0.6, 0.65, 0.75, 0.8]
Rushing to purchase the phone with a mindset of trying, I just get it. It is the wife's gift for Qiqiao Festival. It is very small in the hand, quite suitable for girls. The system is very smooth and feels quite adapted to Apple's operating habits. I buy it roughly and do not pay attention to headsets and charging equipment. They need to be purchased separately. Running speed: very fast! Appearance: with phone case and protector Photo effect: Too many functions, no know how to use	Evaluation officer	[0.6, 0.65, 0.75, 0.8]
...	...	...

4.2. Data Analysis

Among the 1000 reviews in the initial review dataset, there are 453 positive reviews, 50 negative reviews, and 497 moderate reviews. The distribution of their opinions is shown in Figure 4. PLUS users account for 58% of the total reviews, evaluation officers account for 37.5%, and ordinary users account for 27.7%. The average value of initial opinions in these 1000 online reviews is 0.637.

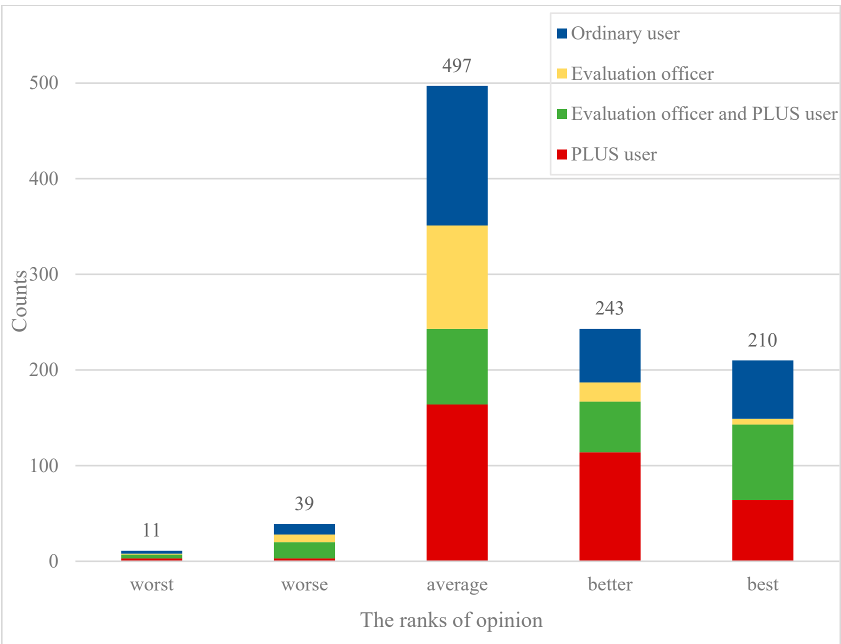


Figure 4. The distribution of review opinions.

The rank of reviewers can affect the degree to which recipients trust the review. If the reviewer is relatively authoritative and experienced, his or her posted reviews will have more influence on the information received by recipients. Reviewers are divided into "evaluation officer and PLUS user", evaluation officer, PLUS user, and ordinary user according to their different identities in the shopping platform. The distribution of the reviewer groups is shown in Table 7.

Table 7. The distribution of the reviewer groups.

Types	Professionalism (*cr*)	Size/Person	Scale
Evaluation officer and PLUS user	1	232	23.3%
Evaluation officer	0.8	143	34.8%
PLUS user	0.6	348	14.3%
Ordinary user	0.5	277	27.7%

4.3. Analysis of Evolution Results

Given the thresholds $\tau = 0.05$ and $\varepsilon = 0.995$, the group opinions are considered to converge when the difference between the consumer opinions in the group is less than 0.005, and all evolution results are averaged over 30 runs. The opinion values of 1000 reviews are regarded as the initial opinions of the recipients and the opinions of the reviewers. There is an independent and non-repetitive interaction between the receiver and the reviewer. The number of interactions is denoted as Time. According to Equations (4)–(10), the purchase intention of the consumer group evolves, and the evolution process and results are shown in Figure 5.

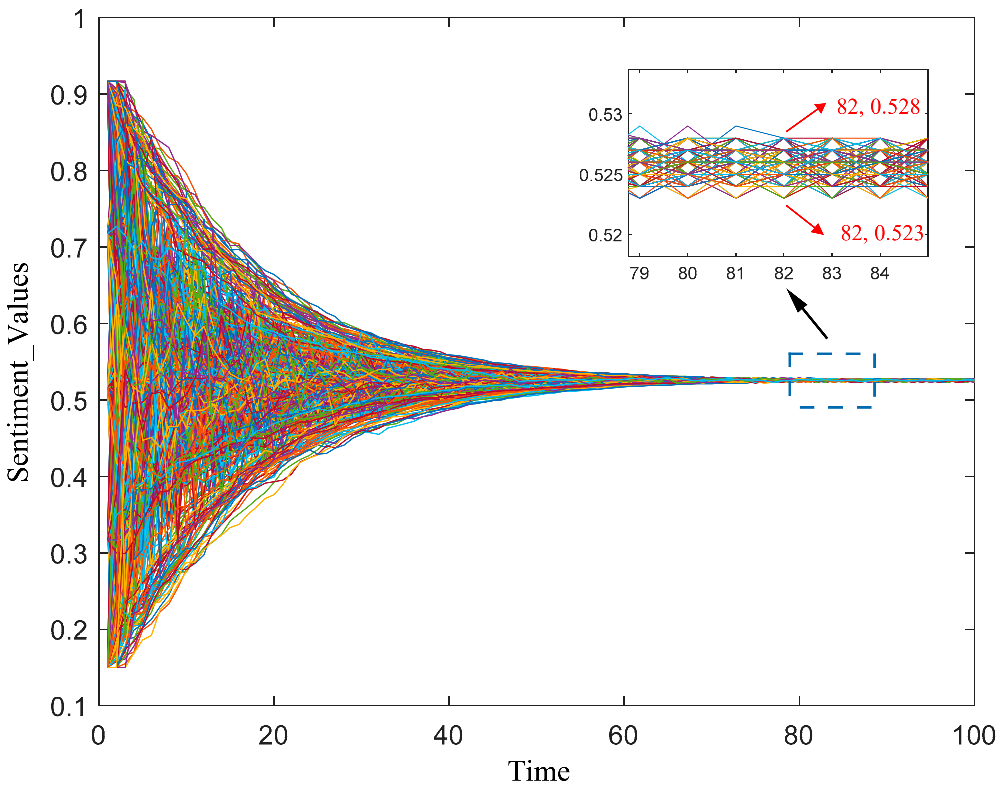


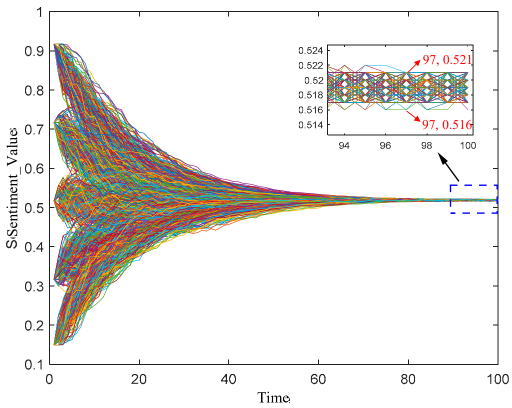
Figure 5. Evolution of purchasing intention of consumer groups.

As shown in Figure 5, the converged value of consumers' willingness to purchase after interaction fluctuates around 0.523–0.528, indicating that the purchase intention of consumers in the groups is 'average'. The average value of an initial opinion is 0.63 according to the distribution of reviewers' initial evaluations. This indicates that the evolved willingness value is smaller than the initial willingness value. Consumers' willingness to purchase is decreasing. Through the evolution model and the "negative bias" mechanism, the final result presented by consumers is lower than the initial opinion value, in line with expectations. As shown in daily online shopping, once negative opinions appear in the reviews, consumers will pay more attention to negative opinions, which is shown as a decrease in opinion value.

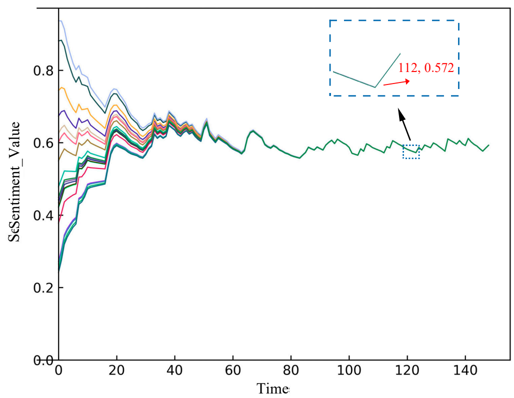
4.4. Sensitivity Analysis

4.4.1. Recipient Personality Coefficient

To gain a more fundamental understanding of consumer purchase intention evolution influenced by recipient and reviewer, lots of simulation experiments are carried out with 1000 reviews. All evolution results are averaged over 30 runs. Different parameters are set to observe the degree of change in consumers' purchase intention. The recipients are divided into three types according to the personality for risk preferences [35]. Specifically, the three categories include stubborn, balanced, and sheeple consumers. Stubborn consumer denotes a person who is not easily influenced by external information and has a hard time changing his or her opinion. The balanced consumer denotes a person who is more rational and unbiased when receiving external information, whether positive or negative information. The sheeple consumer denotes a person more likely to follow the crowd and accept the views of others to a greater extent. The coefficient of recipient personality is denoted cr. $cr \in [0.1, 0.5, 0.9]$ in each dimension denote stubborn, balanced, and sheeple consumers, respectively. We run the simulation to obtain the stabilized opinions, which are shown in Figure 6.

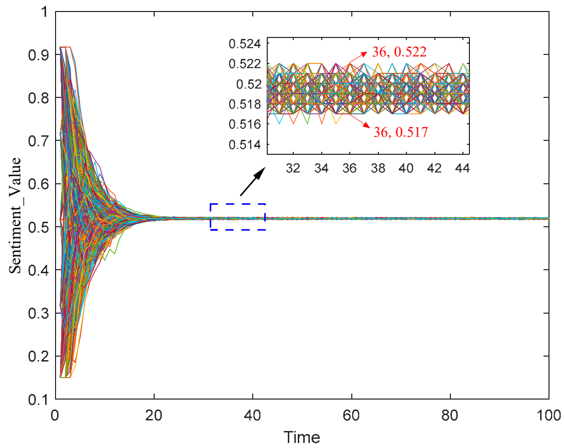


(a1) Evolution of consumer group

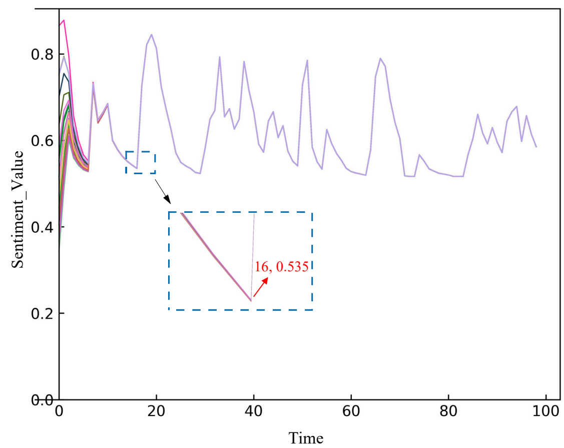


（a2） Individual consumer evolution

a The stubborn consumer



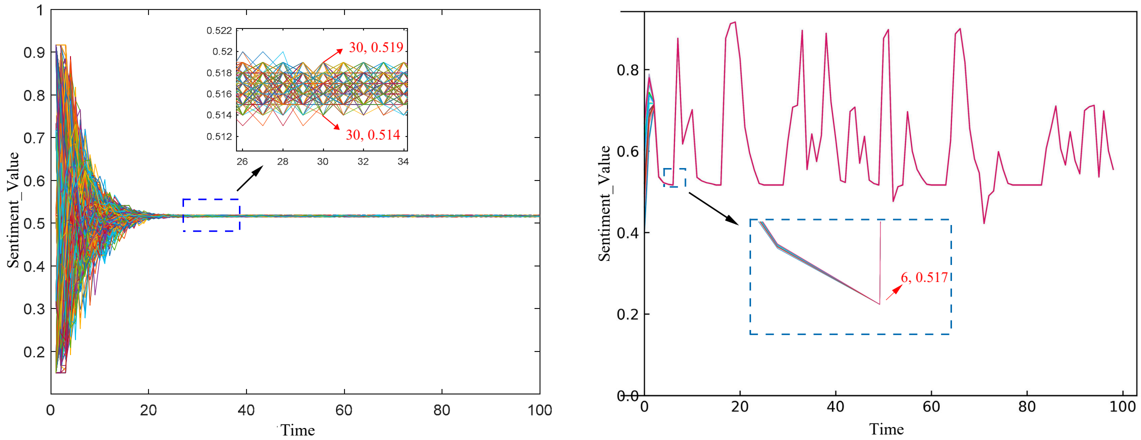
(b1) Evolution of consumer group



（b2） Individual consumer evolution

b The balanced consumer

Figure 6. *Cont.*



(c1) Evolution of consumer group

（c2）Individual consumer evolution

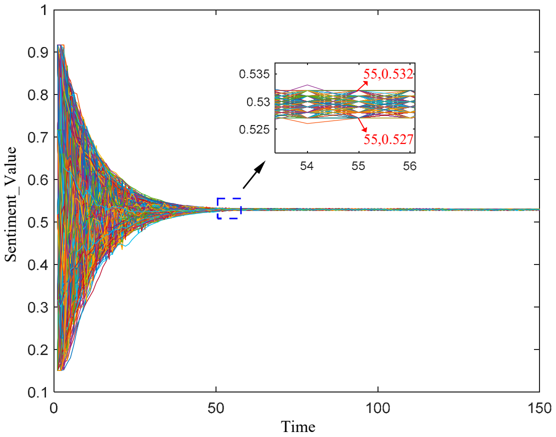
c The sheeple

Figure 6. Evolution of consumer purchase intention with different recipients.

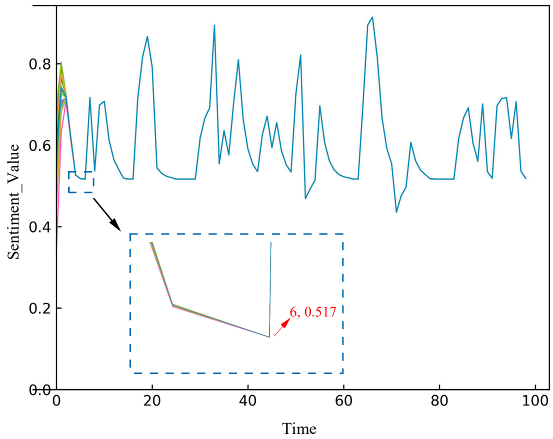
As Figure 6a1,b1,c1 shows, recipient personality has a significant impact on the convergence time of the purchase intention of consumers, while they have little influence over the convergence value. In three groups of recipients, the convergence values all fluctuate around 0.518, indicating that personality characteristics of the consumer group have little effect on their final purchase intention values. For the convergence time, the stubborn consumers keep the longest, and their purchase intention changes more gently. The convergence time is longer for the balanced consumers than for the sheeples, indicating that the balanced consumers deal with reviews rationally and make rational judgments, while the sheeples tend to follow the crowd without thinking. The opinions of balanced consumers and the sheeples both converge slightly slower, while the sheeples are more likely to trust the reviews, and thus make faster purchase decisions, as shown in Figure 6b2,c2. The change in purchase intention of individual consumers with different personality characteristics is shown in Figure 6a2,b2,c2. Their purchase intentions all gradually converge and show consistent changes. The change of purchase intention is more moderate for the stubborn consumers, while the change of balanced consumers and sheeples is relatively large, which has a strong relationship with their personality characteristics. Balanced consumers act more rationally when receiving others' opinions, while sheeples are too easy to believe in the reviewer's opinion and quickly reach a consensus. Then, the same fluctuation occurs.

4.4.2. Reviewer Professionalism

Reviewer professionalism is the key to consumers' trust in opinion, and the more authoritative the reviewer is, the higher the degree of consumers' trust. The influence of the evolution trend of consumer purchase intention from the different professionalism ranks of the reviewer is shown in Figure 7.

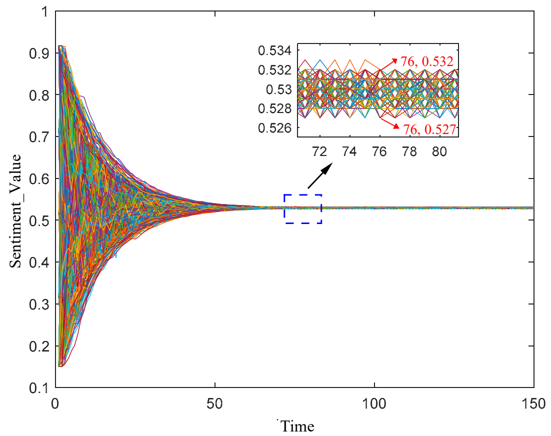


(a1) Evolution of consumer group

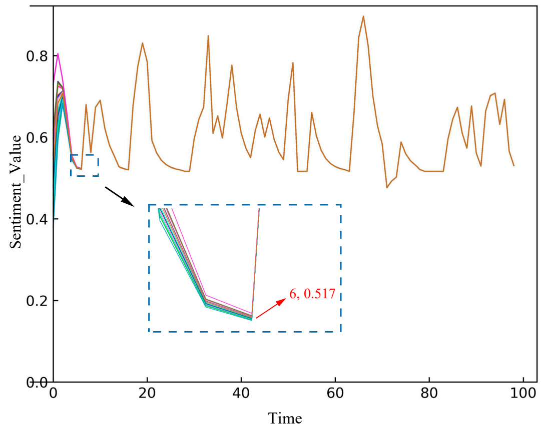


(a2) Individual consumer evolution

a Evaluation officer and PLUS user

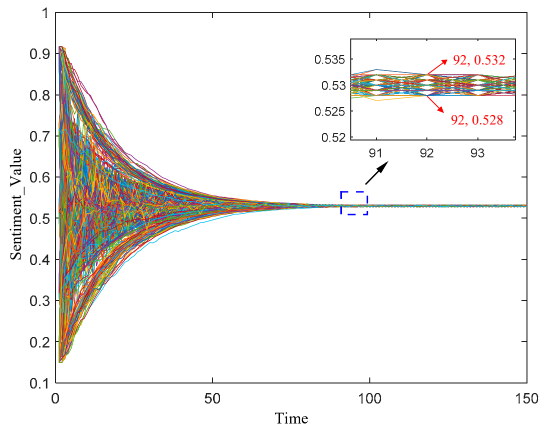


(b1) Evolution of consumer group

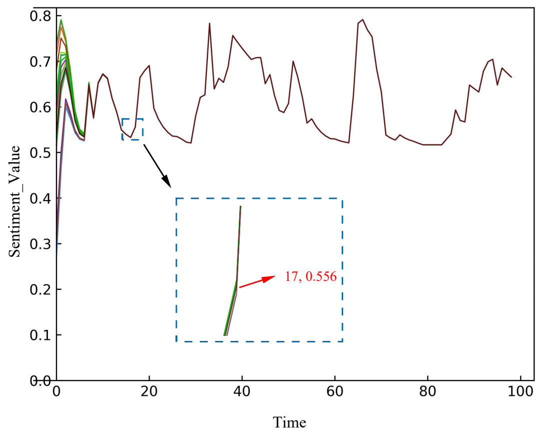


(b2) Individual consumer evolution

b Evaluation officer



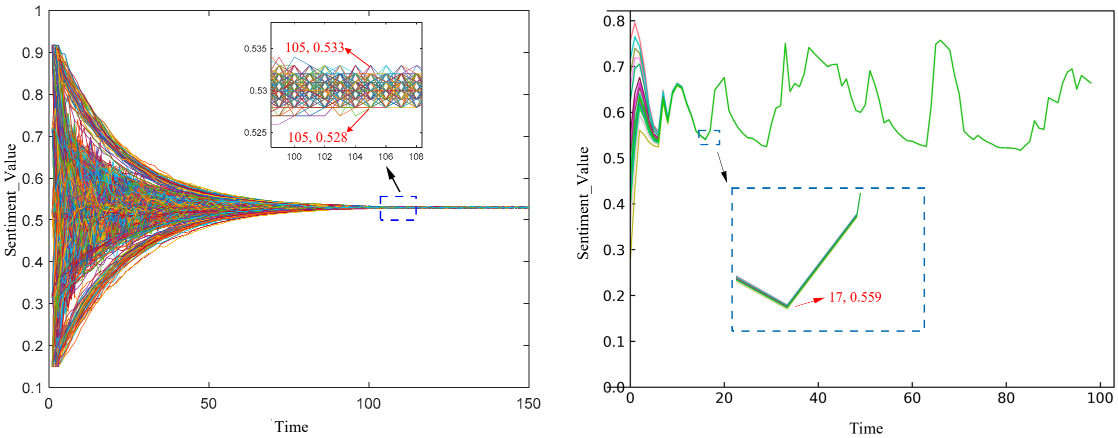
(c1) Evolution of consumer group



(c2) Individual consumer evolution

c PLUS user

Figure 7. *Cont*.



(d1) Evolution of consumer group

(d2) Individual consumer evolution

d Ordinary user

Figure 7. Evolution of consumer purchase intention with different reviewers.

As Figure 7a1,b1,c1,d1 shows, the professionalism of reviewers has little effect on the convergence value of consumer purchase intentions, which are all around 0.53, and the final convergence value is determined by the group's initial view. The professionalism of reviewers has a significant effect on the convergence time of consumer purchase intentions. The status of "evaluation officer and PLUS user" presents greater authority in these reviews, and these reviewers are generally individuals who post more reviews and buy more products. They have higher trust, and recipients can assimilate their review views more easily. Moreover, the convergence time is shorter, and the purchase intention converges the fastest. Compared to the PLUS user, the evaluation officers' willingness to purchase changes faster, the convergence step is shorter, and ordinary users' will to purchase changes the slowest and the convergence step is the longest, as shown in Figure 7a2,b2,c2,d2. Since the influence on the recipient's opinion is subtle when the reviewer is an ordinary user, only when a certain amount is reached will their opinions gradually converge. This is consistent with the change in consumer purchase intention in real life.

The more authoritative the reviewer is, the easier it is for consumers to trust the reviewer's opinion, and the faster and quicker the attitude change in their purchase intentions. The lower the trust level of ordinary users, the slower the evolution will be. All in all, consumers prefer to trust reviewers with greater authority.

4.4.3. Size of Heterogeneous Consumers

Whether the size of the consumer group has an impact on consumer purchase intention is worth exploring in depth. For one thing, we can dig out how the group size of different recipient personalities affects purchase intention in consumer groups. On the other hand, it remains necessary to explore the evolution of the recipient's final purchase intention under different reviewer group sizes. Therefore, it is necessary to explore two aspects of recipient personalities and reviewer professionalism in this paper respectively. Keeping the total sample 1000, increase the number of a certain attribute group n_i proportionally each time, and reduce the number of other attribute groups n_j according to the initial proportion of the group they occupy. Then, the calculation formula of the size of each group is as shown in Equations (11) and (12)

$$n_i = n_i + \alpha \sum_{k=1}^{4} n_k \tag{11}$$

$$n_j = n_j - \frac{n_j}{\sum_{k=1}^{4} n_k - n_i} \times \alpha \sum_{k=1}^{4} n_k \tag{12}$$

where $i, j, k \in \{1, 2, 3, 4\}$ and $i \neq j$. n_i is the number of increasing in an attribute group, n_j is the number of reductions in an attribute group, α is the proportion of increases, and the initial value is 5%. The effect on the evolution of purchase intention when the proportion increases in different recipient characteristic groups is shown in Figure 8.

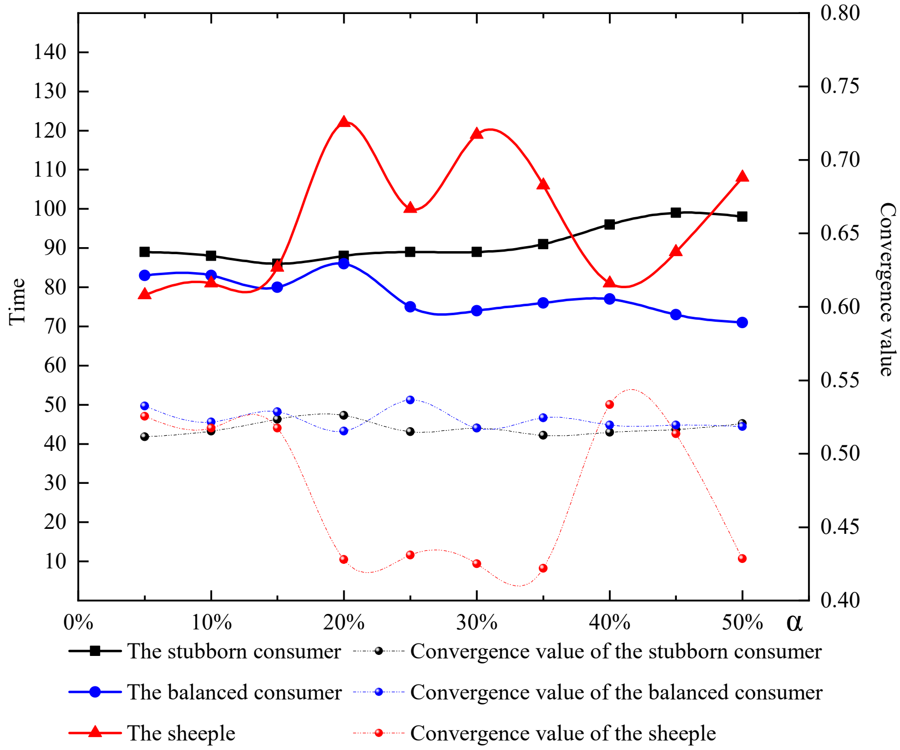
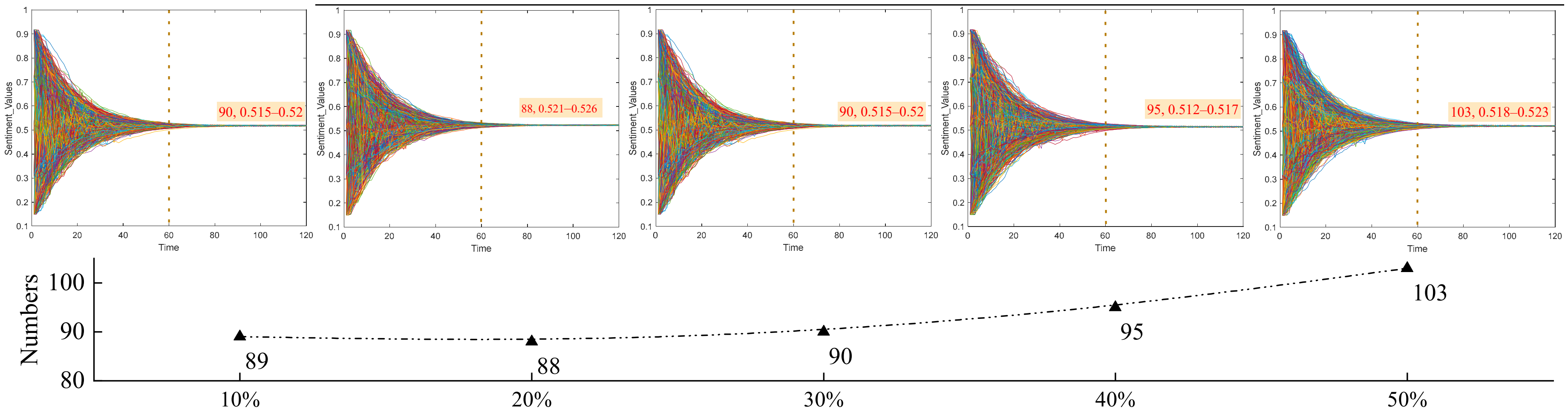


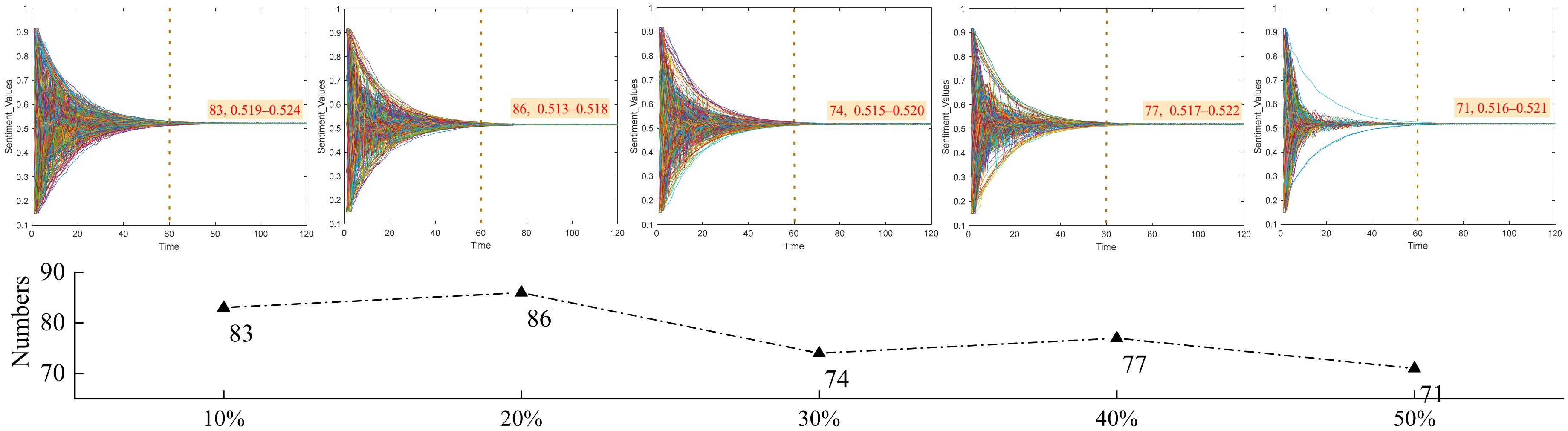
Figure 8. Result of purchase intention evolution with increasing the proportion of heterogeneous recipient groups.

As Figure 8 shows, with the increase in the proportion of recipient groups, the convergence time of the stubborn consumer is longer than that of the balanced consumer, which is greatly related to consumer personality. The stubborn consumers are less assimilated. They need to interact with more people and thus reach a consistent opinion. The convergence time of the balanced consumer tends to decrease with the increase in the proportion of balanced consumers, because as the number of balanced consumers increases, the influence of stubborn consumers and sheeples decreases, and the more the group treats the reviews rationally.

The convergence time of sheeples fluctuates more, and its convergence step has a peak when the proportion of followers grows to 20% and 30%, as shown in Figure 8, which is due to that sheeples will have the phenomenon of following the crowd when interacting with opinions, and they are easier to believe others' views. Sheeples will keep converging to negative views when their opinions converge to negative views. Therefore, the convergence time is longer, and the convergence value is smaller, as shown in Figure 9c. Therefore, as the proportion of sheeples gradually increases, the degree of assimilation among consumer groups will be higher, and their purchase intention will easily appear in the reverse viewpoint situation. Once the purchase intention of consumers evolves to a negative view, it takes longer for the interaction to stabilize. This is related to the characteristics of the group of sheeple, who tend to follow the crowd and always believe in other people's opinions. As the purchasing intention of consumers develops in a positive direction, its convergence value shows little change. If the consumer evolves to a negative direction, the time of evolution will be longer, and the consumers will be more negative. This indicates that the personality of recipients can not only affect the change time of consumers' purchase intention, but may also cause a sharp change in the overall consumer intention.

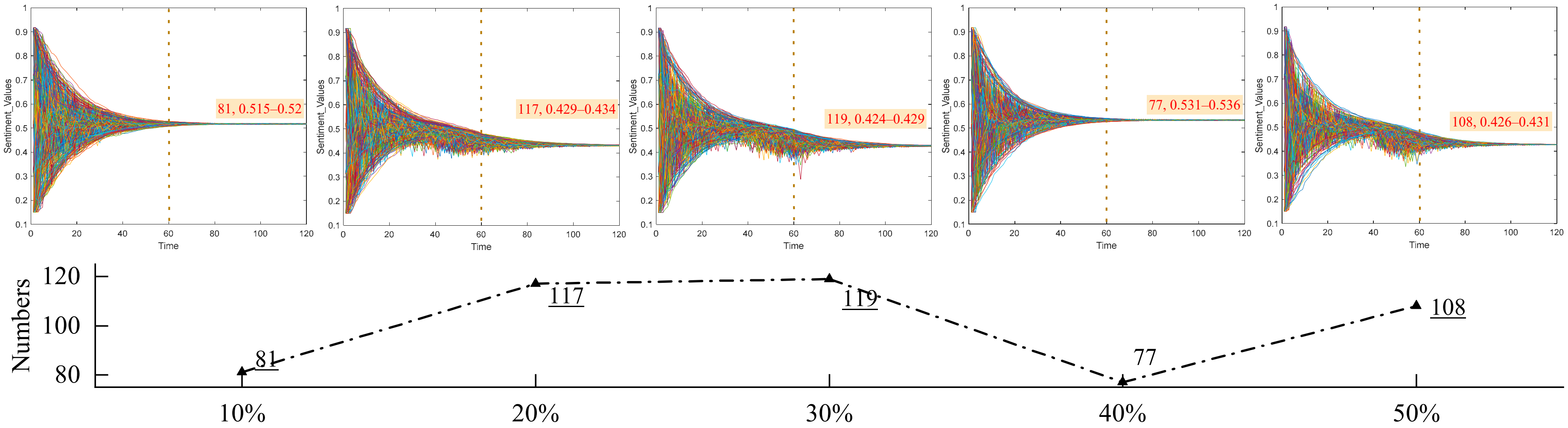


(**a**) The stubborn consumer



(**b**) The balanced consumer

Figure 9. *Cont.*



(**c**) The sheeple

Figure 9. Evolution curve of purchase intention of recipients in the increase of the different proportion.

Based on the characteristics of the four reviewer groups, the influence of the professionalism of reviewers on consumers' purchase intention is explored, and its sensitivity analysis curve is shown in Figure 10.

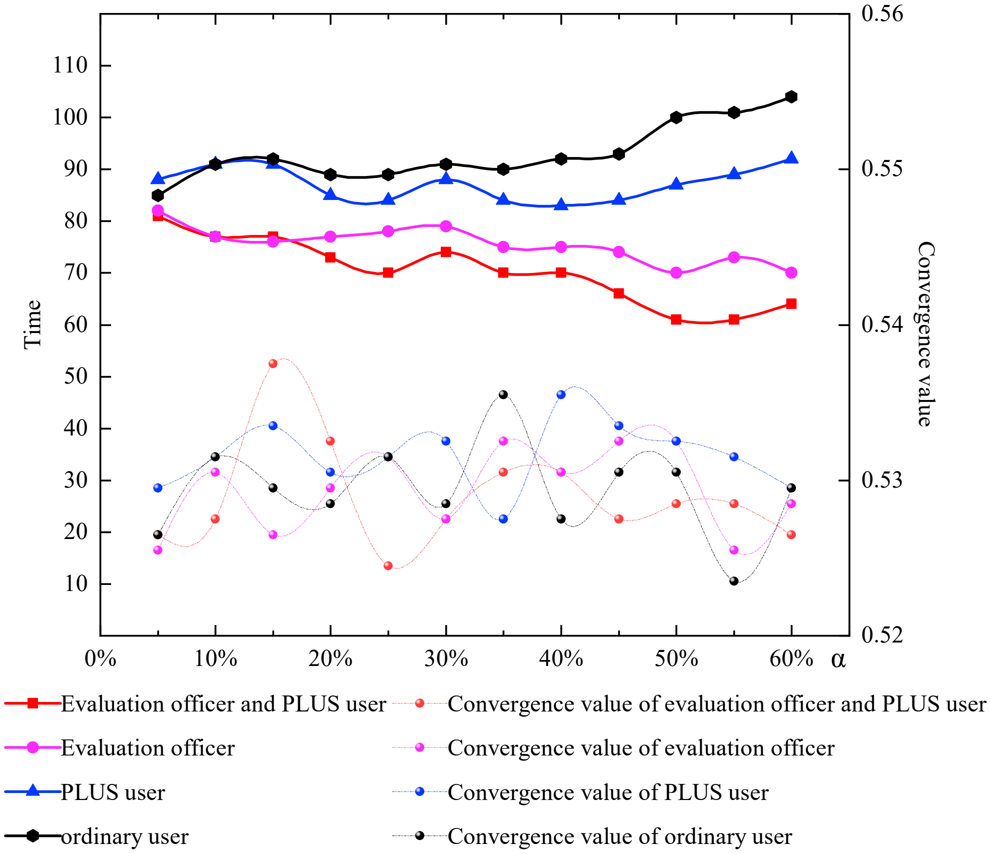
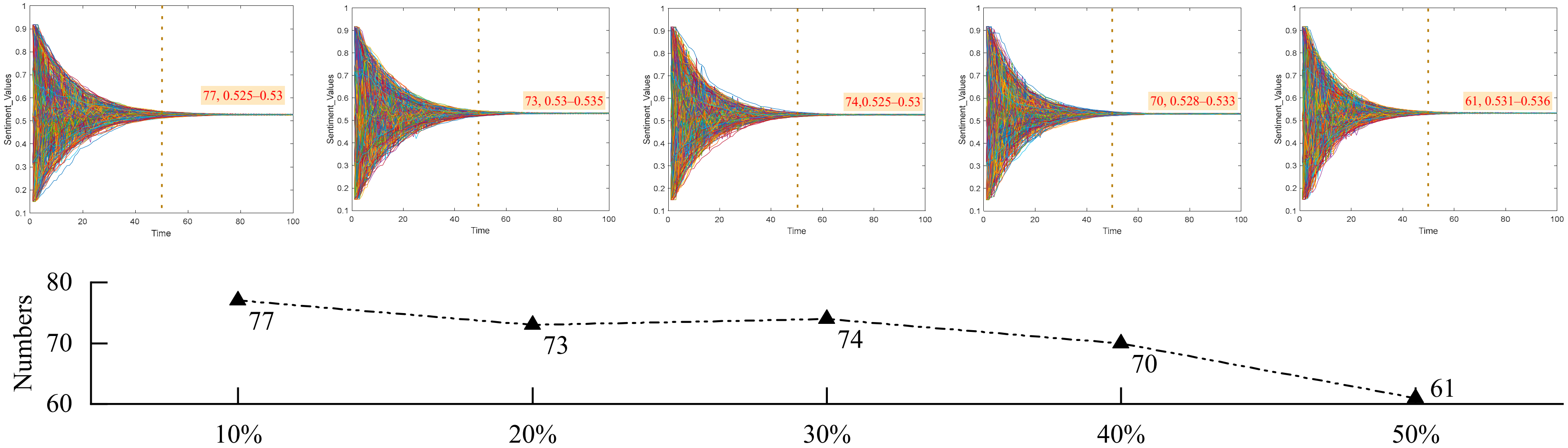
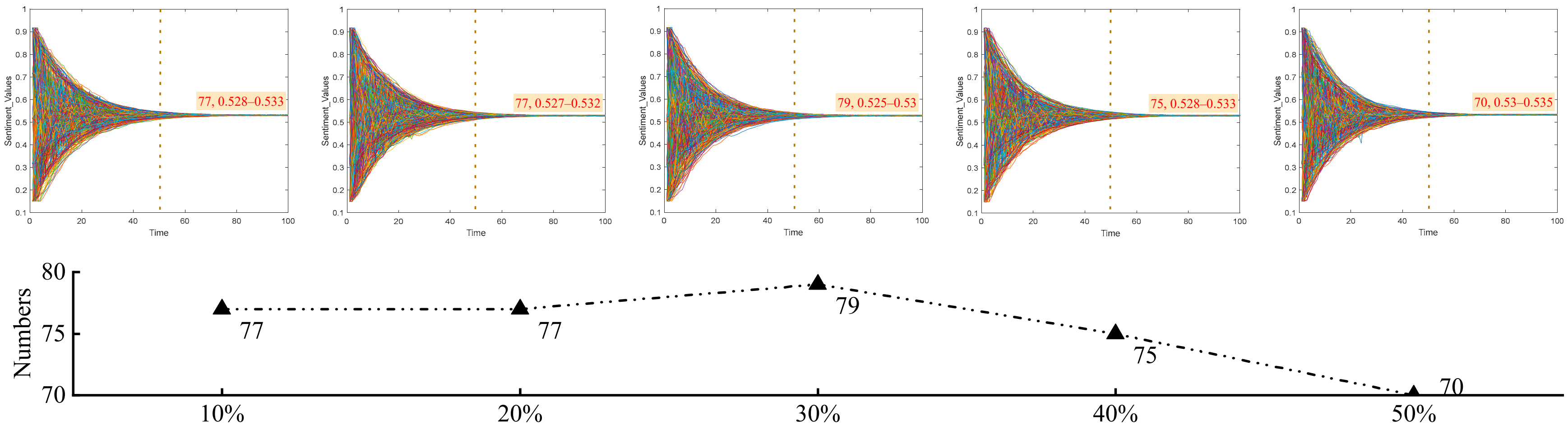


Figure 10. Evolution curve of consumer purchase intention of reviewers in the increase of the different proportion.

As shown in Figure 10, the convergence times of ordinary users and PLUS users go up steadily with the increase of their proportion (as shown in Figure 11c,d), which indicates that the reviews posted by ordinary users and PLUS users are less assimilated by the recipients, and the changes of the recipients' purchase intentions are slower and take longer to evolve. The convergence time decreases the fastest as the proportion of the "evaluation officer and PLUS user" increases, as shown in Figure 11a. While the convergence time shows a decreasing trend as the proportion of evaluation officers increases, as shown in Figure 11b. This is due to the slightly weaker influence of evaluation officers on the recipient's purchase intention compared to "evaluation officer and PLUS user", whose authority is slightly weaker than that of dual-identity reviewers. Therefore, the decreasing trend is not significant. Increasing the proportion of PLUS users as well as ordinary users shows an increasing trend in its convergence time while increasing the proportion of "evaluation officer and PLUS user" shows a decreasing trend in its convergence time. This is also consistent with the fact that the stronger the reviewer's professionalism and the more authoritative their identity, the more recipients are willing to trust and follow the wishes of the reviewer to purchase, as well as make the final purchase decision more quickly. The convergence value of consumers' purchase intention always fluctuates between 0.52–0.54 with a small range. It follows that increasing the proportion of homogeneous reviewers can effectively increase the purchase intention for products, although leading to a small change in the overall consumer intention. This indicates that the authority of reviewers can only affect the change time of consumers' purchase intention, and there is little effect on the group intention value.



(**a**) Evaluation officer and PLUS user



(**b**) Evaluation officer

Figure 11. *Cont.*

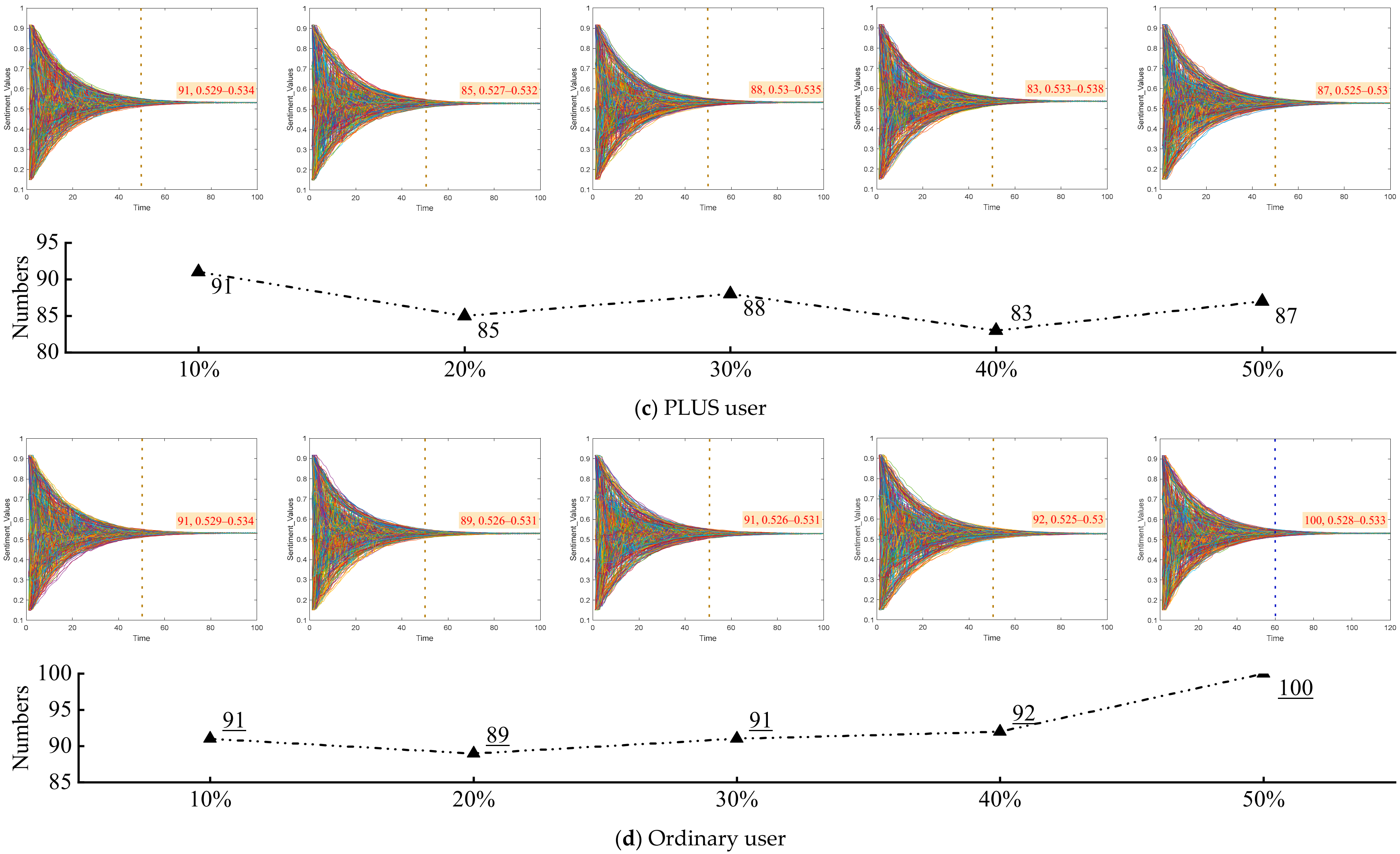


Figure 11. Evolution curve of consumer purchase intention of reviewers in the increase of different proportions.

5. Conclusions

The improved D-W model comprehensively analyzes the interactive relationship among recipients, online reviews, and reviewers to explore how the purchase intentions of consumers change dynamically under the influence of online reviews.

The results of study show: (1) The evolution of purchase intentions takes longer when the recipient is stubborn. The convergence time of purchase intentions is shortest when the recipient is sheeple. However, there is a special case that when the number of the sheeple consumers increases, there is a great tendency to negative comments, and the overall convergence time is very long. The balanced consumers take slightly longer compared to the sheeple consumers. Recipients need less convergence time in the evolution of purchasing intention when receiving reviews from reviewers who are "evaluation officer and PLUS user". However, the convergence time of evolution is longer when recipients receive reviews from ordinary users, and the more professional the reviewer is, the shorter the convergence time is. (2) The purchase intentions of stubborn, balanced, and sheeple consumers all show a downward trend when increasing their proportion in a group. Moreover, increasing the proportion of the sheeple consumers will have a greater impact on group consumers' purchase intention with a faster decline in purchase intention. Increasing the proportion of homogeneous reviewers can effectively increase the purchase intention of products. This indicates that the authority of reviewers can only affect the change time of consumers' purchase intention, leading to a small increase in the overall consumer intention.

From the case results of the simulation, the evolution model of consumers' purchase intention is effectively verified in terms of accuracy, and the results fit the reality of the moment. When the quantitative structure of the recipient and reviewer groups is changed, the purchase intention of the consumer group will be greatly influenced. Increasing the presence of authoritative persons in the group can effectively accelerate the formation of the group's purchase intention. In marketing management, enterprises can properly encourage authoritative reviewers to make comments, which can effectively promote the formation of group word-of-mouth. In addition, if there are a large number of sheeple consumers in the group, the negative reviews can have a greater impact on the enthusiasm of the group, and it is difficult for the group to reach a consensus on the purchase intention. The positivity of reviews can effectively increase the willingness of the follower group to actively buy. This study provides insightful guidelines for marketers with practical implications for approaching emerging markets via online review initiatives.

There are still limitations in this study. First, opinion mining technology is explored in this study about the searchable products with certain attributes. For experimental products, relevant contents of mining technology should be adjusted on the basis of this study. The change mechanism of consumers' purchase intention for experimental products can be explored in future research as the complement to this related field. In addition, during the process of browsing online reviews, consumers' purchase intention may not only be affected by online reviews, but also by other external factors, such as shopping platforms and emotional factors. In this study, the main impact of consumers' browsing online reviews is discussed without considering other potential external factors. These can be further discussed in future research.

Author Contributions: Conceptualization, N.Z. and P.Y.; methodology, N.Z. and P.Y.; validation, N.Z. and P.Y.; formal analysis, N.Z. and P.Y.; data curation, P.Y.; writing—original draft preparation, N.Z., P.Y. and Y.L.; writing—review and editing, N.Z., P.Y. and Y.L.; supervision, N.Z. and Y.L.; project administration, N.Z., P.Y., Y.L. and W.G.; funding acquisition, N.Z. and W.G. All authors have read and agreed to the published version of the manuscript.

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Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

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