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Opinion evolution of online consumer reviews in the e-commerce environment

Yan Wan[1] · Baojun Ma[1] · Yu Pan[2]

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Abstract Online consumer reviews play an important role in shaping potential customers' purchase decisions in e-commerce. Previous studies have analyzed the influence of online consumer reviews on sales, mainly considering factors such as reviewers' and viewers' profiles, information provided, and product features. However, there are relatively few studies that discuss how online consumer reviews interact with each other and how consumers' opinions evolve over time. This paper proposes an opinion evolution dynamics model that is applicable to online consumer reviews in the e-commerce environment by taking into account influencing factors such as viewer reading limits, review sorting and releasing strategies, convergence parameters, review posting possibilities, and confidence thresholds. Using multi-agent simulation based on the proposed opinion evolution dynamics model, the paper discusses how these factors affect viewers' opinions, and the opinion evolution process itself. Finally, conclusions and managerial implications of the simulation results are discussed.

Keywords Opinion evolution · Online consumer review · Opinion dynamics · Multi-agent simulation

✉ Baojun Ma
mabaojun@bupt.edu.cn

Yan Wan
wanyan@bupt.edu.cn

Yu Pan
13311887777@163.com

[1] School of Economics and Management, Beijing University of Posts and Telecommunications, Beijing 100876, People's Republic of China

[2] School of Business and Management, Shanghai International Studies University, Shanghai 200083, People's Republic of China

1 Introduction

Reports from various sources indicate that consumers are making more and more online purchases, and when making purchase decisions they are increasingly relying on consumer product reviews listed on e-commerce webpages under the product descriptions. Furthermore, these online consumer reviews (OCRs), as Internet word of mouth, play an important role in potential customers' purchasing behaviors not only online, but also offline [1]. O2O (online to offline) is becoming more and more popular, especially in China. Every month, more than 10 billion pages providing comments on products such as restaurants, entertainment, shopping, gymnasiums, and child care are read by potential customers making purchases both online and offline. OCRs have become one of the most important and effective means of information sharing between consumers, and also between consumers, merchants, and producers [2]. Consumers can obtain detailed comments about goods and services from other consumers, while merchants and producers can collect information provided by their customers regarding the pros and cons of their products with the aim of better understanding consumers' requirements and identifying areas for improvement. Therefore, it is valuable to conduct research into the OCR domain so as to better understand how reviewers' opinions influence future sales.

A considerable amount of research has been carried out into why OCRs are important and how they affect customers' purchase decisions. To summarize, the major features of OCRs that can affect consumers' purchase intentions can be grouped into the following three categories.

(1) Characteristics of *reviewers and viewers* (e.g. personal characteristics and their relationship) are considered to be influential factors by many studies, but with different patterns of influence. (a) Reviewers' characteristics can affect the influence of their reviews on consumers' decisions *through other factors*, including trust [3] and the strength of the interaction between the reviewer and the viewer [4]. (b) The characteristics of reviewers and viewers can also become *moderators* affecting the influence of OCRs on consumers' decisions and sales. Major characteristics identified include a reviewer's reputation and exposure [5], viewers' involvement [6], Internet experience [7], and gender [7, 8].

(2) *Review information* Common influential characteristics of review information include quantity of reviews, linguistic characteristics, a reviewer's disclosure of identity-descriptive information, semantic orientation, and valence of review information. It has been found that large amounts of review information [9–11], prevalence of reviewer disclosure of identity-descriptive information [12], and easily readable reviews [13] can increase consumers' purchase intentions. Semantic orientation (and the ratio of positive to negative reviews) and its intensity can also exert influence on consumers [6, 10, 14, 15], while the patterns of influence and effects may differ (e.g. negativity bias) [9].

(3) Features of *goods* Price, brand, popularity [7], and category (e.g. experiential or non-experiential goods) [9] will all affect consumers' purchase intentions,

but to differing extents and in different patterns. The characteristics of goods are usually considered to be moderators.

However, although these studies help us to understand more about OCRs and their relationship to sales, they only examine how reviewers' opinions influence sales, not viewers' opinions. We think that viewers' opinions are affected by previous reviews, and once the viewers submit their opinions, those opinions will affect new viewers. In other words, opinion evolution is a dynamic process. However, there is scant research on opinion dynamics in e-commerce OCRs.

More specifically, this paper focuses on the following three tasks.

(1) C*onstruction of an opinion evolution model* Based on previous studies in the OCR domain and observations of opinion interaction processes on existing mainstream e-commerce websites, an opinion evolution dynamics model applicable to e-commerce OCRs is constructed.
(2) *Analysis of factors influencing opinion evolution* We discuss how certain factors may affect opinion evolution based on the opinion evolution model proposed in this paper. Some general characteristics of opinion evolution in the online review environment are identified.
(3) *Exploration of the managerial implications of the results of the factor analysis.* This paper summarizes the influencing factors and patterns identified via the model simulation and analysis, and explores how we can use these results to improve customer service by fine-tuning the influencing factors.

2 Related research on opinion dynamics

2.1 Opinion dynamics

Originating from social physics, opinion evolution dynamics applies the concepts and methods of physics in exploring the origin and evolution of opinions. Every individual will have his or her own opinion on every topic exposed to them, and these opinions are propagated through human interactions. Everybody's opinion will be shaped by everybody else's opinion. Development and evolution of opinions can be observed and analyzed, and that is what opinion evolution dynamics sets out to do.

Factors affecting opinion evolution can be classified into three categories.

(1) The number of people that may affect an agent's opinion and the way in which they do it (i.e. *network topology*). This is determined by the number of people and how they are connected to this agent. Initially, a regular grid (e.g. a one-dimensional or two-dimensional grid) model dominated the analysis [16], but early in the 21st century, models of complex networks [17] or adaptive networks [18] began to emerge, and have since become the most popular interaction topology and most active research area in opinion dynamics.
(2) How an agent's opinion is changed (i.e. *opinion updating*). This depends on (a) how much an agent trusts other people's opinions and (b) different

updating mechanisms. In the Deffuant model, a convergence parameter is defined to indicate how an agent's opinion is shaped by another partially connected agent's opinion [19]. Furthermore, the Hegselmann–Krause model [20] sets up a confidence threshold to indicate that if the difference of two agents' opinions is larger than the confidence threshold, one agent will not trust the other agent, and their original opinions will not be changed by the other's opinion (bounded confidence model). Meaningful conclusions can be drawn about the characteristics of models (e.g. the confidence threshold) in relation to complex networks [21–23]. The persuasiveness of a review as an influencing factor is also studied [24]. As to the mechanism of opinion change, an agent may simply adopt a random agent's opinion that is connected to him, and a model based on this assumption is called the voter model [25]. A majority rule model is developed in which an agent will adopt the views of the majority of a group [26]. The Hegselmann–Krause model assumes that the opinion of an agent is influenced by the averaged view of adjacent neighbors [20]. In the majority rule model, opinions are discrete, and one can only accept or reject an opinion but not find an average, as in the case of a casting vote. However, in the Hegselmann–Krause model, opinions form a continuum and can represent the strength of an emotion, such as being in favor of something [27–29].

Opinion dynamics research employs computer simulations to test the impact of various factors on opinion formation and evolution with different parameters and rules in different situations [30]. Since the early 2000s, opinion dynamics models have been proven effective in areas such as political campaigning and marketing. Bernardes et al. [31] employed the Sznajd model on grids and complex networks, and the simulation results were consistent with the real vote distribution, both being power law distributions with similar parameters. Advertising is another important area in which opinion dynamics finds successful applications. Suppose people are divided into two groups, one representing consumers of commodity A and the other representing consumers of commodity B (a duo-monopoly situation). With advertisements as external factors, a consumer's decision is affected by both the decisions of neighbors and advertisements [32, 33]. Opinion dynamics has also been employed to study how stock prices are affected by market opinions. Hence, it is worth exploring the application of opinion dynamics to OCRs in e-commerce.

2.2 Opinion evolution of online consumer reviews

There are only a few studies examining opinion evolution of OCRs in e-commerce environments. They use the change in consumer ratings collected from e-commerce websites to represent opinion change, and study the behavior change associated with ratings changes, such as changes in the number of reviews posted or posting of more extreme opinions. For example, Moe and Schweidel [34] study how previously posted ratings may affect an individual's posting behavior in terms of whether to post reviews (incidence) and what to post (evaluation), and find that positive ratings environments increase posting incidence, while negative ratings environments discourage posting. Godes and Silva [35] investigate the evolution of online ratings over time and in terms of sequences. They establish that there exist two distinct dynamic processes, one as a function of the amount of time a product has been available for review and the other as a function of the sequences of the reviews themselves. They find that when previous reviews are divided and diversified, subsequent reviews may lead to more purchase errors and lower ratings. Mochon and Schwartz [36] find that a product may be negatively influenced by the quality of the previous product reviewed, but positively influenced by the star rating assigned to that product. Chen et al. find that the relationships between marketing variables and online posting behavior by consumers are different in the early and mature stages. However, the posting behavior they discuss is related to social media rather than e-commerce websites [37].

While the above studies are very interesting in terms of studying behavioral change associated with opinion evolution, no study has been carried out on how previous opinions affect later viewers' opinions, and opinion dynamics theory has not been adopted, although it can be useful in this area.

3 Opinion evolution dynamics model of online consumer reviews in the e-commerce environment

As described in Sect. 2.1, an opinion evolution model can be built with defining features in two areas: (a) *Network topology*: how people are connected with and affect each other; and (b) *Opinion updating*: how an agent's opinion is influenced and changed. These two aspects of the proposed model of opinion evolution dynamics of online consumer reviews in the e-commerce environment are discussed below.

3.1 Network topology

Network topology is the biggest difference between our model and many existing opinion dynamics models. In complex networks, the interaction rules are based on the underlying network, and opinion interactions happen between connected agents, which are fixed. For example, Twitter users can only see tweets from users they follow (i.e. those in their network). However, on e-commerce platforms such as Amazon, the pattern is quite different. Opinion interaction happens through viewing and posting reviews on a public board. Viewers generally have no relationship with the reviewers. A viewer's opinion is influenced by the opinions of previous reviewers at the moment he or she reads their reviews. This implies that how an opinion is influenced depends on how many reviews a viewer reads (assuming that a viewer will not always finish reading all the posted reviews because the total number of reviews can be very large), and how the reviews are sorted to display when he or she reads. These differences in interaction patterns or topologies require us to redefine the interaction rules instead of simply adopting the rules for complex networks. Hence, we have the following influencing factors.

Influencing factor 1: Reading limit m This study considers viewers' reading limits. We assume that viewers will only read a limited number of reviews, and the maximum number of reviews a viewer can read is defined as m.

Influencing factor 2: OCR sorting and releasing strategies We believe that the same set of reviews can have different impacts on a viewer's opinion if they are displayed in different orders and at different times. As a result of the reading limit, a viewer would read different reviews if the reviews were sorted in different orders and released in different batches.

3.2 Opinion updating

In the e-commerce environment, we think that opinion values can be considered as continuous rather than discrete. Furthermore, because potential consumers generally do not know each other, they tend to trust opinions that are similar to their own, but don't trust opinions that are very different. Therefore, opinion dynamics models such as the Deffuant model and the Hegselmann–Krause model are useful because (1) they define opinion as a continuous value $S_i \in [0,1]$ instead of a discrete value, and (2) they are *bounded confidence models*, that is, they set a parameter ε as a threshold so that opinions with absolute differences larger than ε cannot affect each other. Hence, there is another influencing factor.

Influencing factor 3: Confidence threshold ε This parameter indicates the boundaries within which a viewer will believe a review. When the difference between the viewer's opinion and the reviewer's opinion is larger than ε, the viewer will not consider the reviewer's opinion.

In terms of an updating mechanism, the Deffuant model demonstrates an opinion convergence process based on compromise. In each step, an agent i is chosen randomly to communicate with an adjacent agent j (also chosen randomly). If the difference between i and j satisfies $|x_i(t) - x_j(t)| < \varepsilon$, these two agents will update their opinion in accordance with Eq. (1) [19]:

$$\begin{cases} x_i(t+1) = x_i(t) + \mu\left[x_j(t) - x_i(t)\right] \\ x_j(t+1) = x_j(t) + \mu\left[x_i(t) - x_j(t)\right] \end{cases}, \tag{1}$$

where $\mu \in [0,0.5]$ is a *convergence parameter*.

In the Hegselmann–Krause model, people can hear the opinions of all the others and update their opinions accordingly (averaged over all the other opinions). The opinion update equation in the Hegselmann–Krause model is as follows [20]:

$$x_i(t+1) = \frac{\sum_{j:\left|x_i(t)-x_j(t)\right|<\varepsilon} w_{ij} x_j(t)}{\sum_{j:\left|x_i(t)-x_j(t)\right|<\varepsilon} w_{ij}}, \tag{2}$$

where w_{ij} is the corresponding value on agent i's adjacent matrix. It can be seen that agents are totally dependent on others' opinions when updating their own opinion, as in the Hegselmann–Krause model.

In our situation, we think that a viewer will retain his or her opinion, but change it slightly based on the average of all other trustworthy reviews.

Influencing factor 4: Convergence parameter μ The convergence parameter reflects the degree of viewers' trust in reviews. The bigger the convergence parameter μ, the more the viewer's opinion is influenced by others' reviews.

Thus, we propose that opinions on an e-commerce platform are updated as follows:

$$x_p(t) = (1 - \mu)x_p(t-1) + \mu \times (\textit{average of opinions in trustworthy reviews}), \quad (3)$$

where μ is the convergence parameter that reflects viewers' level of trust in reviewers and $x_p(t-1)$ and $x_p(t)$ represent an individual's opinions about the product at times t−1 and t. These parameters are set between 0 and 1.

Furthermore, how much effort an agent is willing to make to post a review must also be considered. This is a unique feature of OCRs in the e-commerce environment. Some online sellers encourage buyers to post reviews to show that numerous products are being purchased.

Influencing factor 5: Review posting possibility e This parameter defines the possibility that a viewer will post a new review each time they visit a review site, and reflects viewers' activity levels. A large review posting possibility also indicates that there are more reviews to be viewed within a specified time period.

3.3 Opinion interaction and updating procedure

After carefully analyzing numerous OCR page setups and opinion interaction procedures on e-commerce websites, an abstract opinion interaction rule is summarized. In this abstract version, only the fundamental steps are reserved, with all minor differences among websites removed. The abstract opinion interaction rules are described as follows.

(1) This model simulates an OCR board for only one product at a time, with a fixed group of agents (i.e. potential customers) involved in opinion interaction. It is assumed that information from other channels (e.g. advertisements, offline communications) has no significant influence on viewers' opinions.

(2) Opinion interaction is achieved by posting and viewing reviews on a public board, where reviews convey reviewers' opinions, and thus viewers' opinions may be affected by previous reviews. Opinion interaction includes two stages, i.e. *receiving* and *propagating*.

- *Receiving stage* In contrast with opinion interaction patterns in online social networks, in which the main factor determining whether two opinions can influence each other is the underlying social linkage, an OCR can only influence viewers' opinions when it is seen (and accepted) by them. There may be hundreds of reviews of a product on an OCR board, but viewers seldom read all of the reviews. Therefore, only the reviews on the first few pages are likely to influence viewers' opinions.
- *Propagating stage* After reading the reviews, there is a possibility that some of the viewers will post their own reviews stating their opinions, which leads to an update of the existing review stream and possible influence on subsequent viewers/agents.

The integrated interaction procedure (including rules and parameters) is shown in Fig. 1. This opinion evolution dynamics model is then programmed as a multi-agent simulation using MATLAB. Each reviewer is treated as an agent.

4 Simulation: analysis of the influence of parameters and sorting strategies of reviews

Based on the opinion evolution model described above, by using multi-agent simulation with MATLAB R2014a, the influence of the four parameters, namely reading limit m, convergence parameter μ, review posting possibility e, and confidence threshold ε, and the initial distribution of opinions, as well as group size, are discussed. Then, the influence of different ways of sorting and releasing reviews is simulated.

4.1 Influence of parameters

The characteristics of opinion dynamics in the OCR environment can be found by analyzing the influence of the main parameters on opinion evolution, as in previous opinion dynamics studies. In the model analysis, different values of the main parameters (as shown in Table 1) are tested to investigate the opinion evolution process and the possible results under various conditions. Hence, 750 combinations ($6 \times 5 \times 5 \times 5$) in total are simulated using MATLAB. Each parameter combination is tested at least five times to ensure accuracy. The values of the parameters are illustrated in Table 1.

Further, different initial distribution patterns of opinions and different group sizes are taken into consideration in the analysis. In the default configuration, each reviewer's (agent's) initial opinion is a random value with uniform distribution on [0, 1].

To investigate the influence of initial distribution patterns (including average value of opinion, range of opinion, and distribution function), two other initial distribution patterns are tested, namely (1) uniform distribution on [0.5, 0.9] and (2) normal distribution N (0.5, 0.08^2).

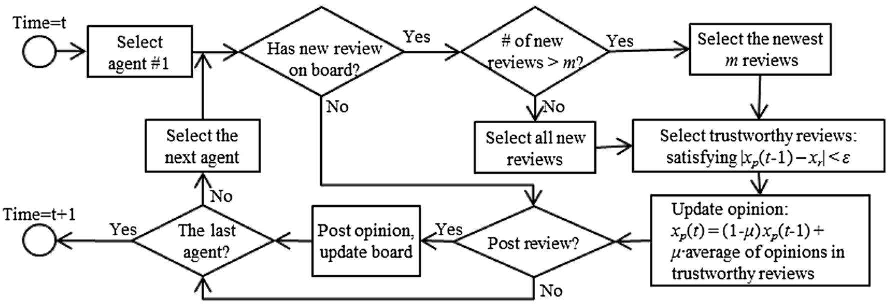


Fig. 1 Interaction procedure in the opinion dynamics model (where $x_p(t)$ represents the agent's current opinion and x_r represents the opinion carried in a review)

Table 1 Parameter values tested (size of group = 600)

	Values					
m	20	40	60	80	100	600
μ	0.2	0.4	0.6	0.8	1.0	
e	0.2	0.4	0.6	0.8	1.0	
ε	0.1	0.15	0.2	0.25	0.3	

$m = 600$ means that all reviews generated in the last period can be read

Two other group sizes (i.e. 200 and 1000) are also tested to investigate the influence of group size on opinion evolution. It should be noted that in testing the influence of group size, the reading limit m is set to $0.1 \times$ (group size) to avoid any overlap of effects from changes in both group size and reading limit.

Using the MATLAB multi-agent simulation based on the parameters outlined above, we analyze the influence of parameters as follows.

(1) *Influence of reading limit m* Reading limit m defines the maximum number of new reviews each viewer can read in each period. It can be seen from Fig. 2 that, in general, m has no significant influence on opinion evolution. However, when m takes relatively small values (e.g. 20 in this experiment), the time

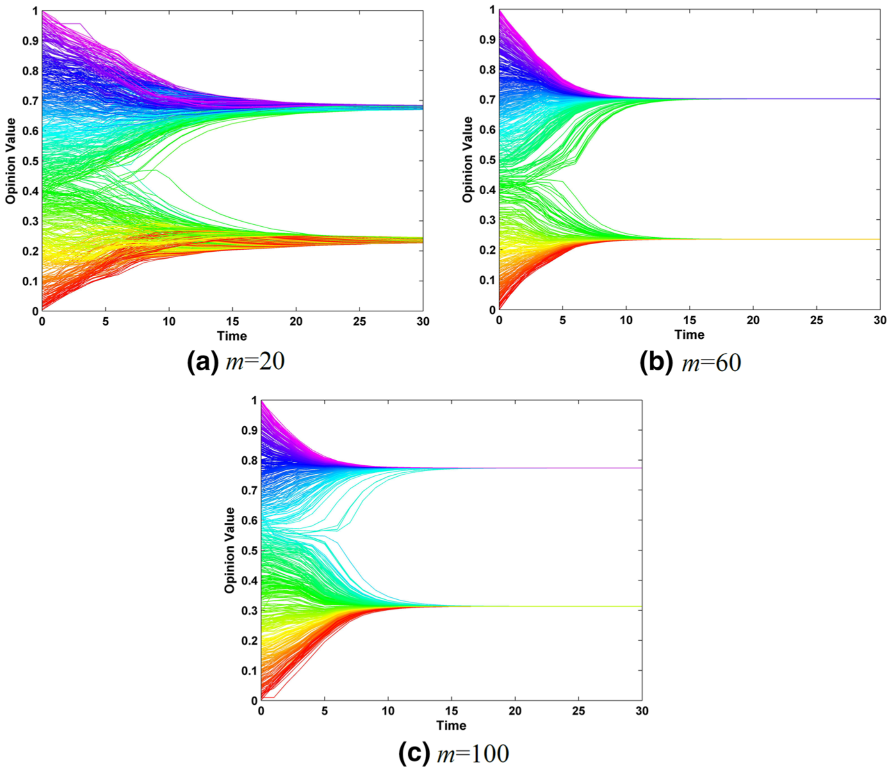


Fig. 2 Influence of m on opinion evolution ($\varepsilon = 0.15$, $\mu = 0.6$, $e = 0.2$)

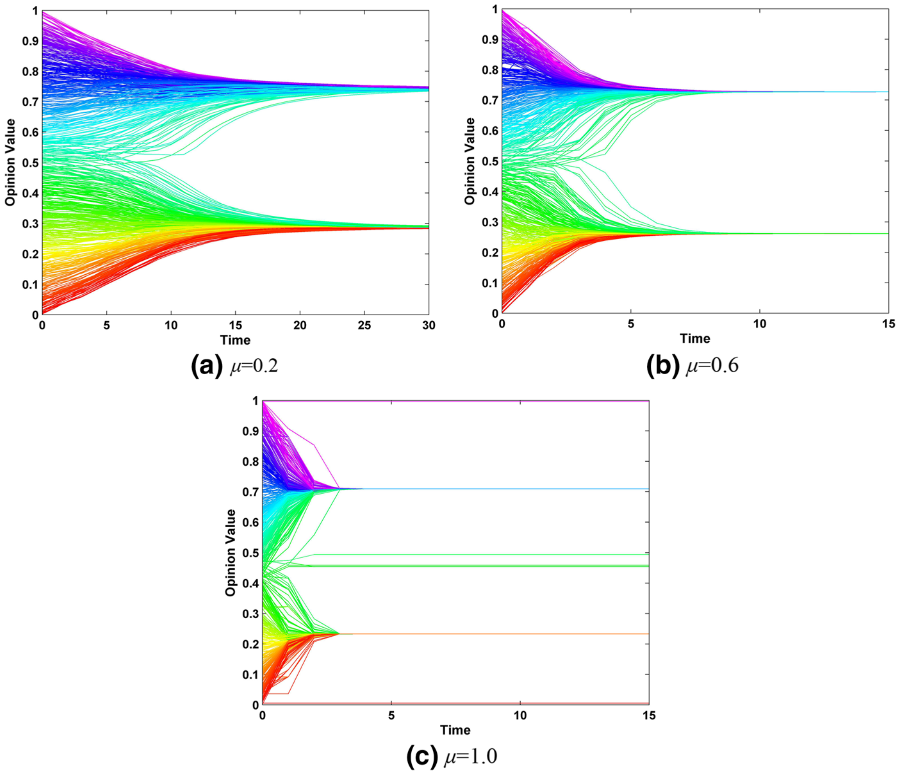


Fig. 3 Influence of μ on opinion evolution ($m = 80$, $e = 0.6$, $\varepsilon = 0.2$)

necessary for opinion group formation may increase. When m reaches 40, opinion evolution no longer seems to be affected by this parameter.

(2) *Influence of convergence parameter* μ Convergence μ reflects how easily viewers' opinions can be changed by the opinions of others. The results show that this parameter only has an influence on the time required for opinion group formation. An increase in μ obviously reflects an increase in the speed of formation of opinion groups. However, when μ becomes large (e.g. 0.8 or 1.0), some individual opinions that are near either 0 or 1, or are located at a distance of at least ε from any existing opinion group, may remain outside any opinion groups (see Fig. 3) because opinions that are initially located near these groups converge to consensus too quickly to affect these extreme opinions.

(3) *Influence of review posting possibility* e Review posting possibility e can influence the number of new reviews appearing at each moment. Simulation results indicate that e has an effect on the number of remaining opinion groups; however, this influence is small. Nevertheless, e can affect the time required for convergence within each opinion group, that is, the time from when the population splits into groups to when consensus is reached within each group. As e becomes large, the time required for convergence within

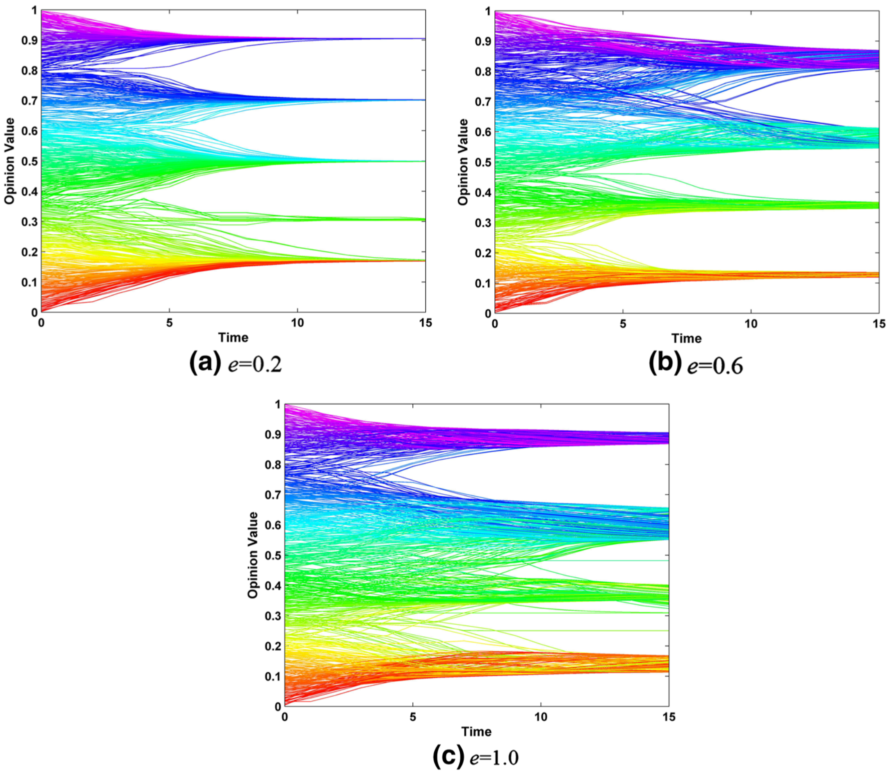
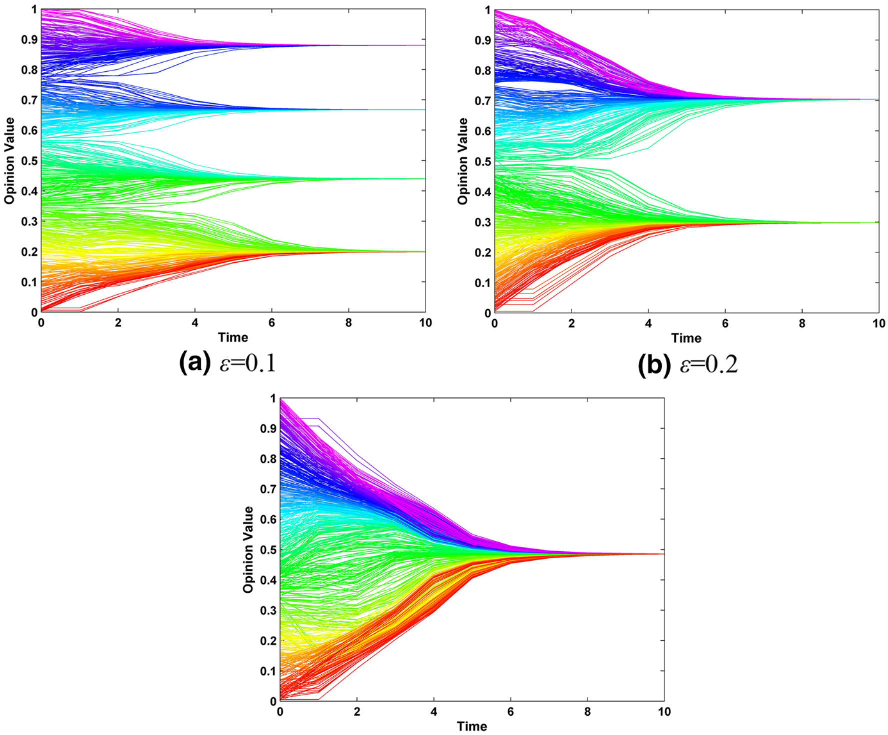


Fig. 4 Influence of e on opinion evolution ($\varepsilon = 0.1$, $\mu = 0.4$, $m = 40$)

groups becomes slightly longer, as seen in Fig. 4. However, this influence is only obvious when the convergence parameter μ is large.

(4) *Influence of confidence threshold* ε The confidence threshold ε reflects agents' (viewers') open-mindedness, which defines the boundary within which a viewer will trust a review. Previous studies have found that this parameter has considerable influence on the number of opinion groups (groups of agents with similar opinions) remaining after opinion evolution. In this study, ε also has considerable influence on the number of remaining opinion groups, independent of the values of μ, e, and m. The number of remaining opinion groups decreases as ε increases. When $\varepsilon \geq 0.3$, consensus can always be reached, that is, only one opinion group will result from opinion evolution (see Fig. 5). Simulation results also indicate that ε has no significant effect on the time required for opinion group formation. However, if there is only one remaining opinion group (i.e. global consensus is reached), the time required for opinion group formation will decrease as ε increases.

(5) *Influence of initial distribution of opinions* The distribution function and average of initial opinions may have an effect on the opinion evolution process and the distribution of the remaining opinion groups. Hence, the



(a) ε=0.1 (b) ε=0.2

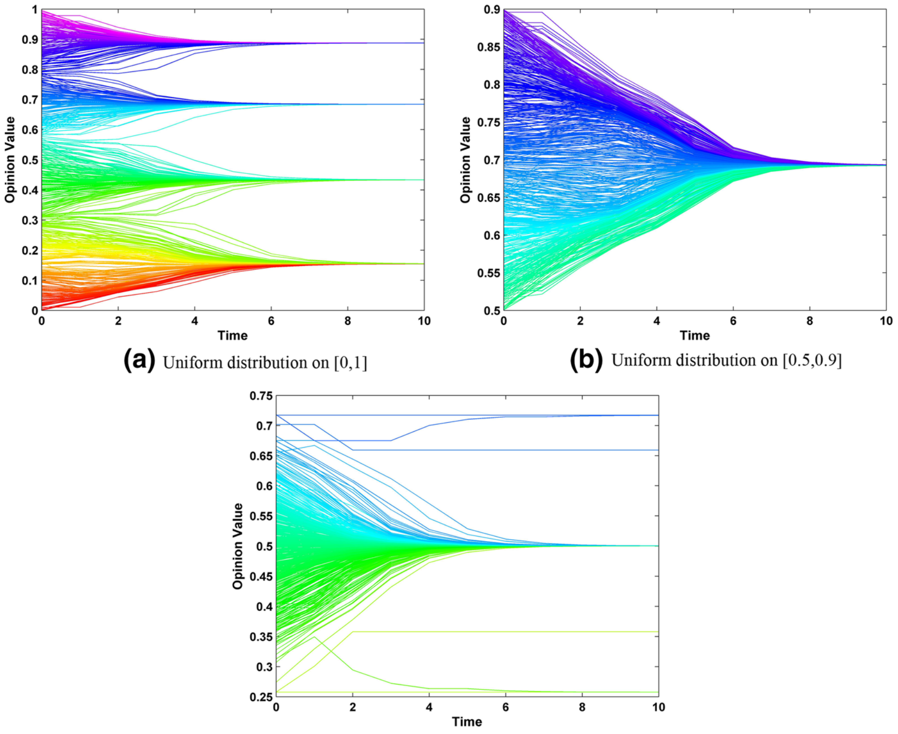
(c) ε=0.3

Fig. 5 Influence of ε on opinion evolution ($m = 80$, $e = 0.2$, $\mu = 0.6$)

influence of the initial opinion distribution is investigated from the following three aspects (see Fig. 6).

- *Average* of initial opinions. The average of initial opinions can obviously influence the average of the remaining opinions.
- *Range* of initial opinions. As the range narrows, it becomes increasingly easier to reach global consensus (i.e. a reduction in the number of opinion groups remaining). Narrowing the range of initial opinions can also accelerate the process of reaching consensus.
- *Distribution functions* of initial opinions. If initial opinions follow a normal distribution, there will be fewer opinions located near 0 and 1 (compared with a uniform distribution), which leads to more extreme opinions existing outside any remaining opinion groups after opinion evolution, because extreme opinions cannot find enough similar opinions with which to communicate.

(6) *Influence of group size* Group size is the number of reviews in total. Simulation using different group sizes (i.e. 200, 600, and 1000) shows that



(a) Uniform distribution on [0,1]

(b) Uniform distribution on [0.5,0.9]

(c) N(0.5, 0.08^2)

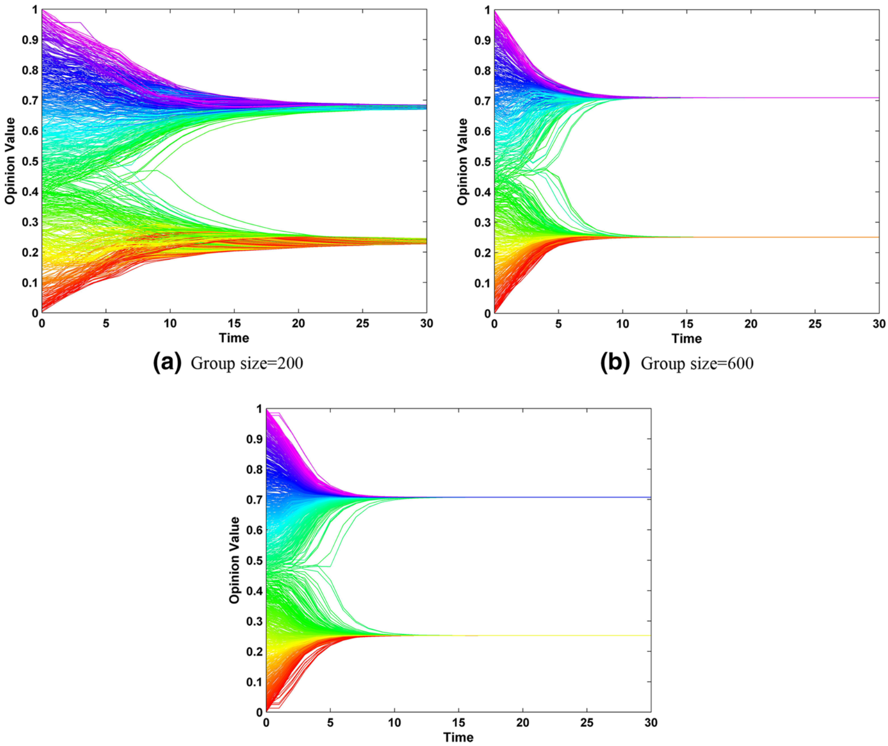
Fig. 6 Influence of initial distribution on opinion evolution ($\varepsilon = 0.1$, $e = 0.6$, $\mu = 0.6$, $m = 60$)

group size has no significant or obvious influence on the process and result of opinion evolution (see Fig. 7).

4.2 Influence of sorting and releasing strategies of OCRs

Here, two review-related organizing aspects are discussed: (1) different review-sorting and organizing strategies, namely temporal sorting (i.e. the newest review is ranked first) and vote-based sorting (i.e. the review attracting the most votes from viewers is ranked first), and (2) one-by-one release or batch release (i.e. buffering new reviews until the accumulated number of new reviews exceeds a predetermined threshold). These two aspects are implemented by adjusting the rules of the proposed model accordingly and simulated using MATLAB. Sorting strategies are compared using different sets of input values. The conditions that are considered and the corresponding input values are shown in Tables 2 and 3, respectively.

The results indicate that adopting different review-sorting strategies influences opinion evolution. Figure 8 illustrates the simulation results using the input values of the above condition #4. It shows that compared with the temporal sorting strategy, the vote-sorting strategy will result in steadier group opinions evolving



(a) Group size=200

(b) Group size=600

(c) Group size=1000

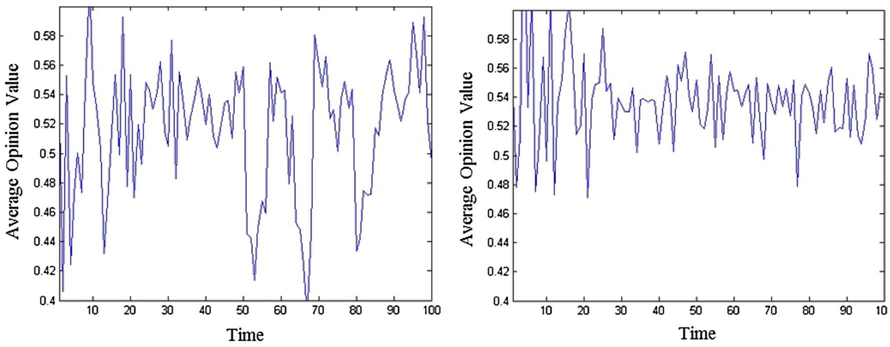
Fig. 7 Influence of group size on opinion evolution ($\varepsilon = 0.3$, $e = 0.4$, $\mu = 0.2$, $m = 0.1$*group size)

Table 2 Conditions considered in the analysis of review-sorting strategies

#	Product value	Opinion matches product value?	Variance of initial opinion
1	High	Yes	Small
2	High	Yes	Large
3	High	No (opinion value is lower)	Small
4	High	No (opinion value is lower)	Large
5	High	No (opinion value is higher)	Small
6	High	No (opinion value is higher)	Large
7	Low	Yes	Small
8	Low	Yes	Large
9	Low	No (opinion value is lower)	Small
10	Low	No (opinion value is lower)	Large
11	Low	No (opinion value is higher)	Small
12	Low	No (opinion value is higher)	Large

Table 3 Input values used in the analysis of review-sorting strategies

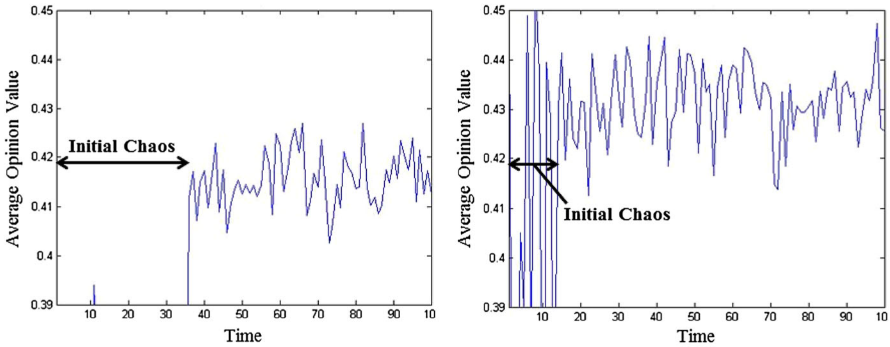
#	Product value	Average of initial opinion	Standard deviation of initial opinion
1	0.5	0.5	0.15
2	0.5	0.5	0.7
3	0.5	0.3	0.15
4	0.5	0.3	0.7
5	0.5	0.7	0.15
6	0.5	0.7	0.7
7	0.3	0.3	0.15
8	0.3	0.3	0.7
9	0.3	0.1	0.15
10	0.3	0.1	0.7
11	0.3	0.5	0.15
12	0.3	0.5	0.7



(a) Temporal sorting (b) Vote sorting

Fig. 8 Comparison of review-sorting strategies (using the input values of condition #4)

over time. That is, variations in group opinions over time are relatively smaller if the vote-sorting strategy is adopted. This influence can be more obvious if the variance in initial opinions is large. Under the vote-sorting strategy, reviews posted in the early period are more likely to receive votes from consumers than later reviews, and hence remain on top of the review board in later periods and receive even more votes. Simulation results show that the reviews with the most votes and listed on the top of the board are indeed those posted in the early period. The influential reviews (i.e. reviews on top of the board) are almost fixed, which leads to limited variations in group opinions over time. This phenomenon is called the Matthew effect, and companies such as Amazon have taken action to avoid it. In the early stage of a product's introduction, instead of allowing one negative review to receive too many 'yes' votes and develop too much credibility, Amazon rotates a few early critical



(a) Batch release **(b)** Pure vote sorting

Fig. 9 Influence of the batch release strategy (using the input values of condition #3)

reviews as being most helpful to online shoppers, letting them share 'yes' votes. Thus, each one will receive an average of a factor or two fewer votes than the most helpful favorable reviews, which decreases the credibility of the most helpful critical reviews in general [38].

The batch release strategy is said to be effective in minimizing the influence of extreme reviews on viewers' opinions by showing several reviews at the same time instead of showing a review immediately after it is posted by a consumer. This study investigates the influence of this strategy on opinion evolution under different conditions (see Tables 2, 3), and it proves the above statement. Figure 9 illustrates a sample of simulation results using the input values of condition #3.

5 Numerical verification

In Sect. 4.1, using simulation based on the opinion dynamics model we propose, we can see that opinions will gradually converge to a steady state; that is, the opinions will gradually form several straight lines as shown in Fig. 7, although they vary widely at the beginning. In order to verify this phenomenon, we collected data from an e-commerce company to see whether opinions really do evolve and eventually converge to a few steady states, as the above simulation results illustrate.

We selected the 100 best-selling products from Amazon.com for the period February 1996 to June 2014 and examined their OCRs. Apart from the review text, each item also includes productID, reviewID, rating (on a scale of 1–5), and postTime (time the review is posted). These 100 products can be classified into five categories, and there are 330,959 reviews in total, as shown in Table 4. ProductID, rating, and postTime are used in our analysis.

First, product ratings are clustered into three classes: good (5* and 4*), average (3*), and bad (2* and 1*). Then, we calculate the percentages of the total number of reviews each month that fall into each of the three classes and plot these percentages over time. Data smoothing is carried out to avoid extreme fluctuations, as follows:

Table 4 Descriptive statistics for the 100 best-selling products from Amazon.com (February 1996–June 2014)

Product categories	Number of products	Number of reviews
Electronics and software	69	237,348
Books	21	72,449
Home and tools and supplies	8	17,173
Health and personal care	1	1706
Sports and outdoors	1	2283
Total	100	330,959

Online consumer review

Max	Min	Mean	SD	Total
13,856	1599	3309.59	2,153.873	330,959

$$y_{n'} = (y_{n-2} + y_{n-1} + y_n + y_{n+1} + y_{n+2})/5 \quad (4)$$

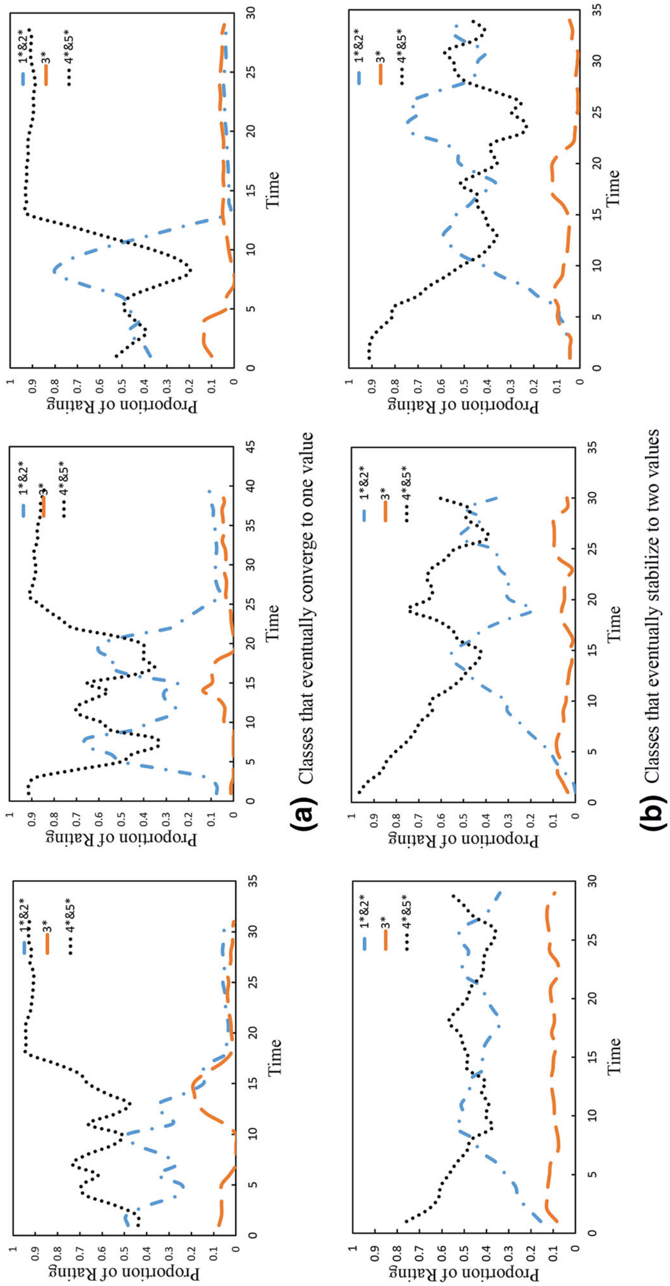
As illustrated in Fig. 10, the horizontal axis represents time and the vertical axis represents the percentages of reviews in each grade.

The patterns of convergence are clearly demonstrated in Fig. 10. Figure 10a shows that product classes eventually converge to a steady state, which implies that most customers share the same opinion on a product. Figure 10b illustrates that product classes eventually converge to one of two states instead of a single state, implying that customers are constantly divided in their opinions on a product, and these opinions are at the extremes of the spectrum.

6 Conclusions and managerial implications

Our findings have important implications for both academic research on OCRs and for online retailing practitioners. From a theoretical point of view, we have identified four important factors affecting opinion evolution and have proposed an opinion dynamics model, which simulates the process of opinion evolution of OCRs in the e-commerce environment. The model assumes that consumers' opinions rest on a continuum, rather than being a binary choice, and there are thresholds for trusting or not trusting a review. It can be used to test the development of new review display strategies or even new marketing measures, as long as the initial parameter values are set to suit the target e-commerce platform.

From a practical point of view, results from the simulation of the opinion dynamics model can be used to enlighten online sellers' management of OCRs. As mentioned earlier, when previous reviewers' opinions are very different, these reviews may lead to confusion, and eventually purchase errors and lower ratings. This is understandable from the consumer psychology point of view whereby high expectations may result in low levels of customer satisfaction, and low expectations may result in fewer purchases. Therefore, it would be desirable for the opinions to



(a) Classes that eventually converge to one value

(b) Classes that eventually stabilize to two values

Fig. 10 Evolution of product ratings over time converge to a stable state quickly, since the stable state can serve as a proxy for the real value of the product. In this respect, the simulation results and their managerial implications can be summarized as follows.

(1) Different ways of sorting and organizing OCRs have an effect on opinion evolution.

- In the two sorting and organizing strategies we simulated (i.e. temporal sorting and vote sorting), we found that the vote sorting strategy can lead to a stable evolution of consumers' opinions and reduce possible uncertainty caused by fluctuations in consumers' opinions.
- In the two review releasing strategies we simulated (i.e. one-by-one release and batch release), we found that the batch release strategy can minimize the possible deviation in opinions caused by extreme opinions in reviews and help the opinions to quickly converge to the real value of the product or service. This is especially true in the early stage of product sales.

Therefore, online merchants can list the most useful reviews as voted by viewers on top, and release reviews in batches, especially in the early stage when there are not many reviews available, to reduce fluctuations in opinions.

(2) In terms of major parameters influencing opinion evolution:

- It is found that the optimal number of reviews on a single page is between 20 and 40 (*read limit m*). Too few may increase opinion fluctuations, while too many may mean that they are not read by viewers.
- For experiential products, viewers are open to seeking opinions from the reviews posted by previous customers (*convergence parameter* μ *is high*). Hence, merchants should pay more attention to OCRs.
- First or early impressions matter (*distribution of initial opinions*). Hence, merchants should pay careful attention to the way in which they present their goods. An early, clear, and honest description of their products will help. Once a bad impression is made, it is difficult to repair.

In the future, text mining techniques and sentiment analysis can be employed to obtain empirical opinion values from the text of OCRs, which can be more accurate than a simple vote (some papers state that votes are not so trustworthy). Moreover, the conditions assumed in this paper (i.e. single product, single seller) are a simplification of reality. In future research, more complicated conditions can be investigated to gain a more comprehensive understanding of opinion evolution. If repeated purchases are considered (that is, the focus is not only on opinion evolution over one to two months, but also on a longer evolution period), temporal sorting may become attractive because it can reflect temporal variations in product values. These changes can be implemented by adjusting the rules and parameters of the basic model proposed in this paper. In terms of sorting customer OCRs, some websites provide viewers with the opportunity to choose either temporal sorting or vote sorting, while others offer only one option. Due to time constraints, we did not test the hybrid display strategy, but plan to do so in the future.

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