Information Cascades and Online Shopping: A Cross-Cultural Comparative Study in China and the United States

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ABSTRACT

This study investigates and compares the impact of information cascades on online shopping behaviors in China and the United States. In particular, the role of information cascades in moderating the effect of price discounts has been examined and cross-culturally compared. To do so, two 122-day panel data sets were collected from two separate online flagship stores selling a same brand of sports shoes on Tmall.com and eBay.com. The results show that product ranking positively influences the product sales in the online shopping market, which follows the predicted results achieved in information cascades studies. Moreover, information cascades are more prominent for Chinese consumers than for American consumers. The findings also suggest that information cascades have moderated the impact of price discounts on online purchase behavior. However, this moderating effect is also influenced by cultural orientation of online customers. The findings are important from not only a theoretical perspective but also a managerial one.

KEYWORDS

Cultural Orientation, Information Cascades, Online Shopping, Price Discounts

1. INTRODUCTION

Information cascades are the scenario “when it is optimal for an individual, having observed the actions of those ahead of him, to follow the behavior of the preceding individual without regard to his own information.” (Bikhchandani et al., 1992), which can affect product adoption (Duan et al., 2009, Park et al., 2019) and sales (Liu et al., 2016, Liu et al., 2020). The online shopping platforms provide an ideal environment for the occurrence of information cascades (Liu et al., 2016; Simonsohn & Ariely, 2004). On the one hand, different from conventional environment of retail face to face, where consumers can touch products and consult salespeople, transactions take place in an online shopping platform that lays a condition of incomplete information (Khatwani and Srivastava, 2018; Sunder et al., 2019). Moreover, with the rapid development of e-commerce, as online retailers take advantage of virtually unlimited shelf space, competing products’ number in every product type grows in an exponential manner. For online shoppers, they usually find themselves without the time

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and knowledge to do the optimal purchase decision-making, often from dozens or even hundreds of completing products (Ding and Li, 2019). For another, a lot of online shopping platforms offer a lot of information about the choices and product popularity of other online customers. For example, Amazon.com provides a list of bestsellers and posts the sales ranking for each product.

Previous studies have confirmed the effect exerted by information cascades on online purchase behavior (Liu et al., 2016; Simonsohn & Ariely, 2004). However, prior studies focus on information cascades on the online shopping platform in a particular country, such as eBay.com in the United States (Simonsohn & Ariely, 2004) and Tmall.com in China (Liu et al., 2016). In fact, many brand retailers have entered electronic commerce platforms in different countries to sell online. For example, as a sportswear brand, ASICS has online stores on Tmall.com in China, as well as on eBay.com in the United States. Moreover, cross-border electronic commerce is rapidly developing globally. According to iiMedia Research, the global B2C cross-border electronic commerce transaction volume reached US\$95.5 billion in 2019, up 27.5% year-on-year, and the global cross-border online shopping penetration rate reached 51.2% (iiMedia Research, 2019). However, few studies have compared the impact of information cascades in electronic commerce markets in different countries. In fact, consumers in different countries may have different cultural orientations (Deufel et al., 2019; Luo et al., 2014; Wang et al., 2019). The influence of customers' cultural orientation on their cognitions and behaviors has been confirmed by a great many of studies (Deufel et al., 2019; Luo et al., 2014; Moon et al., 2008; Shiu et al., 2015; Wang et al., 2019). Although some recent literature has analyzed the moderating effects of cultural orientation on word-of-mouth behavior (Lee and Choi, 2019), social media usage (Hu et al., 2020), and diffusion of innovations (Pettifor et al., 2017) from the perspective of social impact, there is no research on consumer behavior combined with information cascades and cultural orientation. Due to the important impact of information cascades on online purchase behaviors, online merchants can design their marketing strategies to enable informational cascades to work for, and not against, them (Liu et al., 2020; Liu et al., 2016). Of course, no matter what marketing strategy is adopted, online retailers need to pay certain resources or costs. If the impact of information cascades on online consumer behavior in different countries is not the same, then online retailers that have entered e-commerce in different countries should use differentiated marketing strategies. Next, an important research question is whether the effect of information cascades on online shopping behaviors will be moderated by the consumers' cultural orientation.

The purpose of this study is to empirically test and compare the effect of information cascades on online purchasing behaviors in China and the United States. To do so, two 122-day panel data sets were collected from two separate online flagship stores selling a same brand of sports shoes on Tmall.com and eBay.com. The study is interesting and meaningful in three aspects. Firstly, to our best knowledge, this research is the first to compare the effect exerted by information cascades on online customers with different cultural orientation. Our results show that product ranking positively influences the product sales in the online shopping market, which follows the predicted results achieved in information cascades studies. Moreover, information cascades are more prominent for Chinese consumers than for American consumers. Secondly, we investigate the impact of possible interactions between information cascades and price discounts on online purchase behavior, which are rarely considered in prior studies. Offering price discounts to online consumers has become the most commonly used marketing strategy for online retailers globally, especially in China (Liu et al., 2020). Many studies have explored the influence of price discounts on online purchase behavior. However, there are several conflicting findings. Some studies pointed out that price discounts could provide quality signaling and facilitating product sales in online marketplaces (Luo et al., 2014; Wu et al., 2015; Liu et al., 2020). However, other studies have found that price discounts have no effect or negative effect on promoting and selling online products (Cao et al., 2018; Erdem et al., 2008). Our study provides a new explanation for the mixed results, which often assumes a uniform impact of price discounts on product sales. The findings suggest that information cascades have moderated the impact of price discounts on online purchase behavior. Moreover, this moderating effect is

influenced by cultural orientation of online customers. For Chinese consumers, price discounts have a negative effect when purchasing higher ranking products online, but it has a positive effect when purchasing lower ranking products online. For American consumers, price discounts have no effect when purchasing higher ranking products online, but it has a positive effect when purchasing lower ranking products online. Finally, cross-border electronic commerce is rapidly evolving globally, and the results of this research can provide important practical implications for online retailers and e-commerce platform managers.

2. LITERATURE REVIEW

It is easy to observe the information overload and other people's choices, hence, the information cascades may be salient on the Internet (Duan et al., 2009; Liu et al., 2016; Liu et al., 2019). As a matter of fact, in recent years, the influence exerted by informational cascades on online consumer behavior has been confirmed in a large number of fields such as software adoption (Duan et al., 2009; Onnela and Reed-Tsochas, 2010; Park et al., 2019), online reading (Liu and Zhang, 2014; Liu et al., 2019; Liu et al., 2020), online shopping (Simonsohn and Ariely, 2004; Liu et al., 2016), user rating (Lee et al., 2015; Gao et al., 2017), P2P lending (Lee and Lee, 2012; Zhang and Liu, 2015), and social network (Feng, 2016), as shown in Table 1. For example, Duan et al. (2009) and Park et al. (2019) found that the software choice of online users is greatly influenced by the changing of download ranking. Liu et al. (2019) showed that information cascades are salient on the online reading market. Further research by Liu et al. (2020) found that information cascades are more salient for paid e-books than for free e-books. In the context of online shopping, Liu et al. (2016) found that information cascades are more salient for experience products than for search products. Zhang and Liu (2015) pointed out that information cascades are an important driving factor for the decision of lenders in the P2P lending market. In the context of the social network, the results of Feng (2016) showed that the leader status of ones' online opinion is positively influenced by the number of users one follows and the number of followers one.

However, previous research has focused on the impact of information cascades on online consumer behavior in specific countries. In fact, consumers may have different cultural orientations with different countries. Moreover, some studies have found the moderating role of cultural orientation from the perspective of social impact (Hu et al., 2020; Lee and Choi, 2019; Pettifor et al., 2017). Pettifor et al. (2017) proposed a unique and transparent method to analyze climate change mitigation, which is to merge the effects of social influence into globally integrated assessment models. Lee and Choi (2019) pointed out the difference of cultural and social relationship variables in prediction power between the U.S. and Korean, and the difference has more relation with individual-level cultural orientation compared with national culture. Hu et al. (2020) suggested that it has a positive correlation between proactive personality and individual cross-cultural adjustment through the mediation of cultural intelligence. However, there is no literature on online consumer behavior combined with information cascades and cultural orientation. Currently, cross-border e-commerce has developed rapidly around the world. If the information cascade has different impacts on consumers with different cultural orientations, then online retailers engaged in cross-border e-commerce should use different countermeasures in different countries or regions.

To complement existing research on information cascades, this paper compares the impact of information cascades on the online purchasing behavior in China and the United States from the perspective of cultural orientation. Moreover, due to conflicting findings in the literature analyzing the impact of price discounts on online consumer behavior, we also investigated whether the effect of price discounts would be moderated by the information cascades and whether such moderating effect would be affected by cultural orientation.

Table 1. Summary of prior studies on information cascades in the online market

References	Research context	Data source	Countries	Main findings
Duan et al. (2009); Park et al. (2019)	Software adoption	CNET Download	United States	Software choice of online users is greatly influenced by the changing of download ranking.
Onnela and Reed-Tsochas (2010)	Software adoption	Facebook applications	United States	The social impact process can highly induce correlated adoption behavior among users.
Liu and Zhang (2014)	Online reading	Book.Sina	China	The user clicks of an e-book will be positively influenced by the change of the e-book ranking.
Liu et al. (2019)	Online reading	Yuedu.163.com	China	Information cascades are salient on the online reading market.
Liu et al. (2020)	Online reading	Zongheng.com	China	Information cascades are more salient for paid e-books than for free e-books.
Simonsohn and Ariely (2004)	Online shopping	eBay	United States	Bidders tend to participate in bids that have more bids.
Liu et al. (2016)	Online shopping	Tmall	China	Information cascades are more salient for experience products than for search products.
Lee et al. (2015)	User rating	Flixster	United States	Information cascades can be triggered when a subsequent generates movie rating through observational leaning by others' rating.
Gao et al. (2017)	User rating	TripAdvisor.com	United States	The average rating that an online product has received in the past has a positive effect on the current user's rating.
Lee and Lee (2012)	P2P lending	Popfunding	South Korea	P2P lenders consider the likelihood of a successful auction by looking at participation rates and the number of days from the open date.
Zhang and Liu (2015)	P2P lending	Prosper	United States	Information cascades are an important driving factor for the decision of lenders in P2P lending market.
Feng (2016)	Social network	Twitter	United States	The leader status of ones' online opinion is positively influenced by the number of users one follows and the number of followers one.

3. HYPOTHESIS DEVELOPMENT

3.1. Information Cascades and Online Consumer Behavior

With the rapid development of the business and service industries, consumers often need to choose from a number of competitive products or services. When making decisions, they often have two pieces of information. One is their own understanding of the product or service, which is based primarily on their knowledge or reading of products and services. Due to information asymmetry, this information is often limited or incomplete, making it difficult for consumers to determine the true value of a product or service, especially in the online market. The second is the information represented by the choices of other consumers. The impact of each aspect of information on consumer decision making is determined by its relative strength. If “the influence of others’ actions could be so substantial that it dominates the influence of their own information” (Bikhchandani et al., 1992), information cascades will appear.

In an electronic commerce platform, when selecting products, online customers can see a large number of product information, e.g., product name, product ranking, product description, product price, discounts, sales, review volume, user rating, and so on. Among them, the product ranking reveals the choice of others. Other information is considered to be private information or customers' own information, which can help them generate their own understanding through perceive the product quality and product value. Information cascades will occur if customers cannot do a reasonable decision through private information, and the others' behavior can be easily observed at the same time.

Supposing a simple model that online consumers make purchase decision between two products sequentially, *A* and *B*. The quality of two products is different but at the same price. Moreover, the desirable of the two products are the same to consumers for they have no previous knowledge of product quality. In this scenario, we suppose that each consumer will obtain a noisy signal before purchase decision-making, and the signal is accompanied by probability p , which is greater than 0.5, indicating than the quality of *A* is greater than *B*. In addition, the probability p is the same for all consumers. Hence, the probability of choice product *A* is p for the first consumer. Then, the second consumer will use his or her own information obtained and the result of the first consumer's choice to do purchase decision-making. According to Bayes law, the probability of purchase product *A* for the second consumer is shown in the following equation:

$$\Pr(\text{Second}) = \Pr(A|A, B) = \frac{1/2 \times p \times (1-p)}{p \times (1-p)} = 1/2$$

Specifically, the probability is the same for the second consumer purchasing product *A* or *B*. If the purchase decision is different for the previous two consumers, the choice of product is random for the third consumer. While, if the purchase decision is the same for the previous two consumers, the probability of purchase product *A* for the third consumer can be seen in the following equation:

$$\begin{aligned} \Pr(\text{Third}) &= \Pr(A|A, A, B) \\ &= \frac{1/2 \times p^2 \times (1-p)}{1/2 \times p^2 \times (1-p) + 1/2p(1-p)^2} > \frac{p(1-p)^2 \times 1/2}{1/2 \times p^2 \times (1-p) + 1/2p(1-p)^2} \\ &= \Pr(B|A, A, B) \end{aligned}$$

which demonstrates the higher probability of purchasing product *A* than *B*. In particular, the third consumer has a great probability of purchasing product *A* when the previous two consumers' product choices are both *A*, in spite of his or her own information suggests that the other option is more appropriate for his or her demand, which makes the beginning of the information cascade.

Nowadays, product rankings are commonly provided to customers by e-commerce platforms such as Tmall.com and eBay.com. It is suggested by literature of informational cascades that product ranking indicates many of the actions from previous consumers and will positively influence the followers' decision-making (Liu et al., 2020; Park et al., 2019). A strong signal will be given to later consumers to outweighs their own information if *A* ranks ahead of *B*. Hence, the relative popularity of two products determines the duration and orientation of information cascades. Existing studies pointed out that it worth a mention that popularity refers to the relative ranking of two products rather than absolute sales (Duan et al., 2009; Liu et al., 2019). Hence, product ranking has been used to capture information cascades in many prior studies (Duan et al., 2009; Liu et al., 2016; Liu et al., 2019; Liu et al., 2020; Park et al., 2019). Consistent with these studies, the following hypothesis is proposed to investigate informational cascades when consumers make the online purchasing decision:

H1: Product ranking positively influence the sales of products in the online shopping market.

3.2. Information Cascades and Price Discounts

Due to the intrinsic prevalence of information asymmetry in sellers and buyers, customers often worried about the product quality when they do online transactions (Cao et al., 2018; Fabisiak, 2018; Liu et al., 2016; Shahri, 2019). One solution to solve the problem is that by providing promotions to acquire early customers. Those customers will give informative quality suggestions to help attract other customers. Earlier studies suggest that quality signaling and facilitating product sales can be achieved by the group buying strategy with price discounts (Luo et al., 2014; Wu et al., 2015). In practice, many retailers widely use price discounts to promote products on the e-commerce platforms (Liu et al., 2020). However, existing literature has conflicting results when studying the impact of price discounts on online consumer behavior. Dhar et al. (2007) found that consumers will be attracted by price discounts, which will have a positive impact on subsequent purchase behavior. The results of Xu and Huang (2014) show that the impulse purchase intention caused by price discount is greater than the bonus packs in the online environment. But, a lot of studies find that discounts, or discounted prices, are usually expected as an indication of low quality which will have no effect or negative effect on promoting and selling the products (Cao et al., 2018; Erdem et al., 2008; Rao & Monroe, 1989). For example, Cao et al. (2018) found that discounts offer a great negative influence on the number of vouchers sold on the online daily-deal platforms.

The mixed results found in earlier studies (Cao et al., 2018; Dhar et al., 2007; Erdem et al., 2008; Rao & Monroe, 1989; Xu and Huang, 2014) could be potentially explained by informational cascades theory, which gives an indication that the complexity of relationship between price discounts and product sales is underestimated than previously thought. Instead of suggesting price discounts offers a uniform influence on products, informational cascades theory indicates that the influence is moderated by the level of informational cascades when customers make purchase decisions. If customers purchase a product mainly based on informational cascades, price discounts will have little influence. When information cascades occur, online customers will mainly choose to purchase products with high rankings. So, we can expect that price discounts have no significant effect on the sales of products with high rankings in the online shopping market. Consequently, the following hypothesis is proposed:

H2: Price discounts have no significant effect on the sales of products with high rankings in the online shopping market.

Nevertheless, when shopping online, price discounts can help consumers perceive the quality of products and form their own purchasing decisions that have been confirmed by many studies (Cao et al., 2018; Liu et al., 2020; Luo et al., 2014). Then, if online customers are driven by their own information to select products, price discounts will have a significantly effect. Hence, we can expect that price discounts have a significant effect on the sales of products with low rankings in the online shopping market. Consequently, the following hypotheses is proposed:

H3: Price discounts have a significant effect on the sales of products with low rankings in the online shopping market.

3.3. Information Cascades and Cultural Orientation

Culture is defined by Hofstede (1980) as “the collective pro-gramming of the mind which distinguishes the members of one group or category of people from others.” (pp. 475). Prior studies find that culture is not only a national level phenomenon; it also can be applied to individual level to explain

individuals' cognitions and behaviors (Luo et al., 2014; Yoon, 2009). According to whether consumers are self-centered or group-centered, Hofstede (1980) divides consumers' cultural orientation into two categories: individualism and collectivism. Among them, individualism is defined as "a preference for a loosely knit social framework in which individuals are expected to take care of themselves and their immediate families only," (Hofstede, 1980), and collectivism is described as "a preference for a tightly knit framework in society in which individuals can expect their relatives or members of a particular in-group to look after them in exchange for unquestioning loyalty." (Hofstede, 1980).

Customers with different cultural orientation may emphasize or value different aspects of products and assess product quality in different ways (Wang et al., 2019). Customers are more independent for those with individualistic culture orientation, and they tend to use their own knowledge to evaluate the target problem, and rarely consider other people's opinions (Cho & Kim, 2017; Luo et al., 2014). However, customers prefer to follow the social/group standards rather than their own opinions for those with collectivistic cultural orientation (Cho & Kim, 2017; Luo et al., 2014). All of the above means that in the context of online shopping, collectivist-oriented consumers will refer more to other customers' actions when making purchasing decisions than consumers with individualistic culture orientation. Information cascade theory suggests that the information cascade appears if the others' actions have a significant impact than private information. Hence, we can expect that information cascades will be more prominent for customers with collectivistic cultural orientation than for customers with individualistic culture orientation. A large number of literatures have regarded the cultural orientation of Chinese consumers as a collectivist orientation, while the cultural orientation of American consumers is often regarded as an individualistic orientation (Deufel et al., 2019; Wang et al., 2019). Consequently, the following hypothesis is proposed:

H4: Information cascades will be more prominent for Chinese consumers than for American consumers.

4. DATA

4.1. Data Description

Our datasets for empirical validation of our hypotheses are from Tmall.com (www.tmall.com) in China and eBay.com (<https://www.ebay.com>) in the United States. They are the most mainstream electronic commerce platform of each country, respectively (Liu et al., 2016; Simonsohn & Ariely, 2004).

For the sake of comparison, we collect data from two online flagship stores that sell ASICS sports shoes, which are located on Tmall.com in China¹ and eBay.com in the United States², respectively. There are four reasons for this. Firstly, ASICS is a sportswear brand founded in Japan, which is neither from China nor from the United States. Although Japan and China are both Asian countries, the United States and China have very closed economic and trade cooperation with Japan. Moreover, as a world-renowned sports brand, the sales of ASICS in the United States market (\$830 million) in 2018 are larger than those in the Chinese market (\$490 million) (Netease, 2019). Therefore, Chinese consumers are not more familiar with ASICS brand than American consumers. Secondly, many online flagship stores on ebay.com do not display product rankings or product sales. Many online flagship stores on Tmall.com are in a similar situation. These all bring difficulties to our data collection. The two flagship stores opened by ASICS on these two platforms respectively show the product ranking and product sales, which can provide support for our research. Thirdly, sports shoes are a typical experience product. When consumers buy experience goods online, they face greater uncertainty than search goods. Liu et al. (2016) found that information cascades are more salient for experience products than for search products. Finally, sports shoes are a non-seasonal product, so the data collected are not affected by seasonal factors.

From May 22, 2018 to September 21, 2018, between 19:00 and 21:00, we collected the top 300 product information based on the comprehensive ranking at the ASICS flagship store of Tmall.com. The reason for collecting only the top 300 product information is that previous studies have indicated that online consumers tend to view information on the top 3 pages of the product ranking results (Liu & Zhang, 2014; Liu et al., 2016), and each result page contains 100 sports shoes. The information of the collected products includes comprehensive ranking, product name, product sales, product inventory, review number, user ratings, price discounts, and product collections. The sample of many products in our collected data were missing during May 22, 2018 to September 21, 2018; consequently, the obtained data set forms unbalanced panel data. To ensure the validity of this research, some samples were eliminated, such as review volume is less than three, user rating is zero, and duration in comprehensive top 300 lists is less than 7 days. Excluding the above-mentioned samples, totaling 13,925 data from Tmall.com were remained and consisting of 761 ASICS sports shoes. In the same time interval (from May 22, 2018 to September 21, 2018, between 19:00 and 21:00), we also collected product information from ASICS flagship store on eBay.com. Since the number of products in this store is not very large, and the ranking results are no more than 3 pages, so we collected information about all the shoes in the store. It is worth noting that this store on ebay.com only provides comprehensive ranking, product name, product sales, shoe size and price discounts. In addition, in this store, many products are removed after being sold, so the sample set we get is also an unbalanced panel data set. Finally, we obtained 8,498 data from eBay.com, containing 337 ASICS sports shoes.

4.2. Key Variables

The main variables and related descriptions are provided in Table 2. Among them, $ISale_{i,t}$ measures the incremental sales of product i that appears at t day compared to it appears at $t-1$ day in the ranking lists. $Rank_{i,t-1}$, $Sale_{i,t-1}$ and $Discount_{i,t-1}$ respectively indicate the comprehensive ranking, cumulative sales and price discounts of product i in day $t-1$. For the data set from Tmall.com, $Stock_{i,t-1}$, $Number_{i,t-1}$, $Rating_{i,t-1}$ and $Collection_{i,t-1}$ are used to represent the stock quantity, review volume, user ratings and total collections of product i in day $t-1$, respectively. Referring to Duan et al. (2009), Lee et al. (2015), Liu et al. (2016) and Liu et al. (2019), key independent variables related to the product sales are processed by a one-day lag. This operation is helpful to better embody the responses of online customers to product ranking and price discounts, and their subsequent decisions. In addition, it also contributes to control the potential endogeneity of dependent variables relative to independent variables over the same period. To effectively control the effect of potential outliers, all continuous variables are processed by the natural log-linear transformation. This processing will cause anomalies in the data with a minimum of 0 or 1, thus $(ISale_{i,t} + 2)$ is used to replace $ISale_{i,t}$, and re-named it as $ISale_2_{i,t}$. Likewise, $Rank_1_{i,t-1}$, $Sale_2_{i,t-1}$, $Stock_1_{i,t-1}$, $Number_2_{i,t-1}$, $Rating_2_{i,t-1}$, and $Store_2_{i,t-1}$ are used to replace $Rank_{i,t-1}$, $Sale_{i,t-1}$, $Stock_{i,t-1}$, $Number_{i,t-1}$, $Rating_{i,t-1}$, and $Collection_{i,t-1}$. Previous studies have found that after this treatment, the nature of the regression equation has not changed (Ding & Li, 2019; Duan et al., 2009; Liu et al., 2016).

The descriptive statistics of key variables are provided in Table 3. Pearson's correlation coefficient was used for calculating the correlation matrix of key variables, which are reported in Table 4.

5. EMPIRICAL ANALYSIS AND RESULTS

5.1. Empirical Model

Incremental sales have been used by prior studies to capture the influences of information cascades in the online market (Li & Wu, 2018; Liu et al., 2016). Hence, consistent with these studies, $ISale_{i,t}$ is used as the dependent variable in this research. Differentiating informational cascades from alternative factors that lead to herd behavior, e.g., network effects, has become a pivotal empirical challenge in investigating the effect of informational cascades (Bikhchandani et al., 1992; Duan et al.,

Table 2. Description of key variables

Variable	Description and measure
$ISale_{i,t}$	The incremental sales of product i in day t against that in day $t-1$ in the ranking lists ($Sale_{i,t} - Sale_{i,t-1}$)
$Rank_{i,t-1}$	The ranking of product i in day $t-1$ in the ranking lists
$Sale_{i,t-1}$	The cumulative sales of product i in day $t-1$ in the ranking lists
$Discount_{i,t-1}$	The price discounts (1-current price/original price) of product i in day $t-1$ in the ranking lists
$Stock_{i,t-1}$	The stock quantity of product i in day $t-1$ in the ranking lists (Only available for Tmall data)
$Number_{i,t-1}$	The number of reviews written about product i in day $t-1$ in the ranking lists (Only available for Tmall data)
$Rating_{i,t-1}$	The user ratings of product i in day $t-1$ in the ranking lists (Only available for Tmall data)
$Collection_{i,t-1}$	The total collections of product i in day $t-1$ in the ranking lists (Only available for Tmall data)
$LnSale_2_{i,t}$	$(ISale_{i,t} + 2)$ (log-transformation)
$LnRank_1_{i,t-1}$	$(Rank_{i,t-1} + 1)$ (log-transformation)
$LnSale_2_{i,t-1}$	$(Sale_{i,t-1} + 2)$ (log-transformation)
$LnStock_1_{i,t-1}$	$(Stock_{i,t-1} + 1)$ (log-transformation)
$LnNumber_2_{i,t-1}$	$(Number_{i,t-1} + 2)$ (log-transformation)
$LnRating_2_{i,t-1}$	$(Score_{i,t-1} + 2)$ (log-transformation)
$LnCollection_2_{i,t-1}$	$(Store_{i,t-1} + 2)$ (log-transformation)
$DisLnRank_1_{i,t-1}$	$LnRank_1_{i,t-1} * Discount_{i,t-1}$

Table 3. Descriptive statistics of key variables

Variable	N	Mean	Median	S.D.	Min.	Max.
eBay data						
$ISale_{i,t}$	8498	15.261	4.000	65.286	0.000	1989.000
$Rank_{i,t-1}$	8498	36.623	34.000	23.259	1.000	86.000
$Sale_{i,t-1}$	8498	240.219	133.000	370.211	1.000	4187.000
$Discount_{i,t-1}$	8498	0.646	0.644	0.087	0.359	0.813
Tmall data						
$ISale_{i,t}$	13925	31.295	1.000	128.830	0.000	3014.000
$Rank_{i,t-1}$	13925	147.246	146.000	83.363	1.000	300.000
$Sale_{i,t-1}$	13925	1998.744	519.000	4371.585	0.000	34875.00
$Discount_{i,t-1}$	13925	0.336	0.362	0.176	0.000	0.712
$Stock_{i,t-1}$	13925	1366.905	378.00	2863.218	1.000	41471.00
$Number_{i,t-1}$	13925	603.692	142.000	1420.903	0.000	11072.00
$Rating_{i,t-1}$	13925	4.808	4.800	0.146	0.000	5.000
$Collection_{i,t-1}$	13925	3585.002	1149.000	6227.757	0.000	47947.00

Table 4. Correlation matrix of key variables

Variable	1	2	3	4	5	6	7	
eBay data								
1. LnISale_2 _{i,t}	1.000							
2. LnRank_1 _{i,t-1}	-0.503***	1.000						
3. LnSale_2 _{i,t-1}	0.280***	-0.555***	1.000					
4. Discount _{i,t-1}	-0.005***	-0.021	0.025***	1.000				
Tmall data	1	2	3	4	5	6	7	8
1. LnISale_2 _{i,t}	1.000							
2. LnRank_1 _{i,t-1}	-0.357***	1.000						
3. LnSale_2 _{i,t-1}	0.273***	-0.502***	1.000					
4. LnStock_1 _{i,t-1}	0.278***	-0.503***	0.333***	1.000				
5. LnNumber_2 _{i,t-1}	0.251***	-0.462***	0.986***	0.302***	1.000			
6. LnRating_2 _{i,t-1}	-0.031***	0.080***	-0.022***	-0.033***	-0.012	1.000		
7. LnCollection_2 _{i,t-1}	0.274***	-0.481***	0.691***	0.331***	0.678***	-0.035***	1.000	
8. Discount _{i,t-1}	0.046***	-0.097***	0.327***	-0.005	0.327***	0.058***	0.207***	1.000

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

2009; Liu et al., 2019). Previous studies pointed out the significant difference between information cascades and network effects (Duan et al., 2009; Liu et al., 2019). The core point of network effects is that the value of the product increases with the rise of the network size. It suggests that the increase of an online product value comes with an increase of the cumulative sales in the context of online purchase behaviors. According to information cascades theory, important information is constituted by a product's popularity. Specifically, when the popularity of one product exceeds the other and the influence of such popularity outweighs the consumers' own information, which makes the beginning of the information cascade (Bikhchandani et al., 1992; Duan et al., 2009). Different with network effects, there is no impact on informational cascades if the increase in the number of users or the number of products purchased cannot change the relative popularity of the two products. Network effects do not directly cause informational cascades although it gives online consumers greater motivation to follow the herd (Duan et al., 2009). So, in addition to $Rank_{i,t-1}$ and $Discount_{i,t-1}$, $Sale_{i,t-1}$ is also included in the main independent variables. Among them, $Rank_{i,t-1}$ is used to examine the influence of information cascades. $Sale_{i,t-1}$ and $Discount_{i,t-1}$ are used to control for the effects of network effects and price discounts. In order to capture the moderating effect of information cascades on price discounts, the $Discount_{i,t-1}$ and its interaction with product ranking $DisLnRank_1_{i,t-1}$ is used as an independent variable to examine the interplay between information cascades and price discounts.

We modeled the effects of information cascades and price discounts on product sales. The panel-level empirical model is specified in Eq. (1):

$$LnISale_2_{i,t} = \alpha_i + \beta_1 * LnRank_1_{i,t-1} + \beta_2 * LnSale_2_{i,t-1} + \beta_3 * Discount_{i,t-1} + \beta_4 * DisLnRank_1_{i,t-1} + U_i + T_t + \varepsilon_{i,t} \quad (1)$$

where α_i captures the unobserved specific effects of products; β_s are the model coefficient; $\varepsilon_{i,t}$ is the error term.

$LnStock_1_{i,t-1}$, $LnNumber_2_{i,t-1}$, $LnRating_2_{i,t-1}$ and $LnCollection_2_{i,t-1}$ are included in the data set from Tmall.com. Next, in order to analyze the possible effects of these variables, we add them as control variables to Eq. (1), and accordingly, Eq. (2) is constructed:

$$\begin{aligned} LnISale_2_{i,t} = & \alpha_i + \beta_1 * LnRank_1_{i,t-1} + \beta_2 * LnSale_2_{i,t-1} + \beta_3 * Discount_{i,t-1} \\ & + \beta_4 * DisLnRank_1_{i,t-1} + \beta_5 * LnStock_1_{i,t-1} + \beta_6 * LnNumber_2_{i,t-1} \\ & + \beta_7 * LnRating_2_{i,t-1} + \beta_8 * LnCollection_2_{i,t-1} U_i + T_t + \varepsilon_{i,t} \end{aligned} \quad (2)$$

To compare the effect of informational cascades in China and United States, a dummy variable *Culture* is used to represent the cultural orientation of customers. For a Chinese consumer, *Culture* is 1; for an American consumer, *Culture* is 0. In the linear regression model, there are three main ways to introduce dummy variables: addition method, multiplication method and hybrid method combined with addition and multiplication (Dewan et al., 2017). Because the average of incremental sales ($ISale_{i,t}$) shown in the Table 1 is very different between the data set from Tmall.com and the data set from eBay.com (31.295 vs. 15.261), the hybrid approach is used to introduce dummy variables into Eq. (1). Accordingly, the Eq. (3) is constructed, as follows:

$$\begin{aligned} LnISale_2_{i,t} = & \alpha_i + \beta_1 * LnRank_1_{i,t-1} + \beta_2 * LnSale_2_{i,t-1} + \beta_3 * Discount_{i,t-1} \\ & + \beta_4 * DisLnRank_1_{i,t-1} + \lambda_1 * Culture + \lambda_2 * Culture * LnRank_1_{i,t-1} \\ & + \lambda_3 * Culture * LnSale_2_{i,t-1} + \lambda_4 * Culture * Discount_{i,t-1} \\ & + \lambda_5 * Culture * DisLnRank_1_{i,t-1} + U_i + T_t + \varepsilon_{i,t} \end{aligned} \quad (3)$$

5.2. Results

The data that we collected were two-dimensional unbalanced panel data sets. According to the Hausmann test results ($X^2 = 1234.519$, $P = 0.000$), the fixed effects model (FEM) estimates are suitable when using Eq. (1) to perform regression analysis on Tmall data. Hence, we first estimate a FEM of Eq. (1) on Tmall data, and summarize the results in Table 5, Column 2. As shown, the coefficient of $LnRank_1_{i,t-1}$ is negative and statistically significant. The coefficient of $Discount_{i,t-1}$ is negative and statistically significant, and the coefficient of $DisLnRank_1_{i,t-1}$ is positive and statistically significant. The coefficient of $LnSale_2_{i,t-1}$ is positive and statistically significant.

Second, we use Eq. (2) to perform regression analysis on the dataset from Tmall.com. The Hausmann test results also show that FEM is also appropriate ($X^2 = 1185.076$, $P = 0.000$), and the regression results are summarized in Column 3 of Table 5. The results show that after adding all the control variables, the regression results for four independent variables are similar to the results in column 2 of Table 5. Moreover, we also found that the coefficient of $LnStock_1_{i,t-1}$ is negative and significant, which suggests that product inventory has a negative impact on product sales. The coefficient of the $LnCollection_2_{i,t-1}$ is positive and important, indicating that the product collection has a positive impact on product sales.

Third, we estimate a FEM of Eq. (1) on eBay data based on the Hausmann test results ($X^2 = 22.677$, $P = 0.000$). The results are provided in Table 5, Column 4. We find that the coefficient of $LnRank_1_{i,t-1}$ is also negative and statistically significant. The coefficient of $LnSale_2_{i,t-1}$ is also positive and statistically significant. The coefficient of $Discount_{i,t-1}$ is insignificant, while the coefficient of $DisLnRank_1_{i,t-1}$ also is positive and statistically significant.

Based on the results in column 2, column 3 and column 4 of Table 5, we find that the coefficient of $LnRank_1_{i,t-1}$ is both negative and significant. It should be noted that a lower value in $LnRank_1_{i,t-1}$ corresponds to a higher ranking, so the negative coefficient suggests that incremental sales of a online product will increase when its ranking improve, for example, from 2 to 1. This suggests that product ranking has a positive influence on the product sales, supporting H1. We also find that the coefficient of $Discount_{i,t-1}$ for Tmall data is negative and significant, but the coefficient of $Discount_{i,t-1}$ for ebay data is insignificant. This indicates that price discounts have a negative and significant impact on sales of higher ranking products on Tmall.com, however, it have no effect on sales of higher ranking products on eBay.com. Hence, H2 is rejected. The coefficient of $DisLnRank_1_{i,t-1}$ for Tmall.com and eBay.com is both positive and significant. This suggests that price discounts have a positive and significant impact on sales of lower ranking products, supporting H3. We also the coefficient of $LnSale_2_{i,t-1}$ is both positive and significant, indicating that online shopping behavior is also affected by network effects.

As reported in Columns 2, 3 and 4 of Table 5, the absolute value of the coefficient on $LnRank_1_{i,t-1}$ for Tmall data (1.023 and 1.196) is larger than that for eBay data (0.610). This indicates that, when consumers shop online, product rankings may have a stronger impact for Chinese consumers than for American consumers. In other words, information cascades may be more prominent for Chinese consumers than for American consumers. However, whether there is an interaction effect between information cascades and cultural orientation of customers (individualistic and collectivistic) is not examined.

Finally, after removing the inventory quantity, review volume, user ratings, and total collections from Tmall data, we integrated the two data sets into a single sample set. For the sake of comparison, we also estimate a FEM of Eq. (1) for the single data set and summarize the results in Column 2 of

Table 5. Model estimation results

Variable	Tmall data (Eq. (1))	Tmall data (Eq. (2))	eBay data (Eq. (1))
$LnRank_1_{i,t-1}$	-1.023** (0.075)	-1.196*** (0.074)	-0.610*** (0.024)
$LnSale_2_{i,t-1}$	0.073* (0.050)	0.043** (0.016)	0.002* (0.023)
$Discount_{i,t-1}$	-1.831* (0.954)	-0.527** (0.195)	-0.794 (0.701)
$DisLnRank_1_{i,t-1}$	0.191** (0.180)	0.118*** (0.069)	0.005** (0.050)
$LnStock_1_{i,t-1}$		-0.075** (0.005)	
$LnNumber_2_{i,t-1}$		0.062 (0.008)	
$LnRating_2_{i,t-1}$		-0.067 (0.006)	
$LnCollection_2_{i,t-1}$		0.162** (0.068)	
Number of observations	13925	13925	8498
Hausman test	$X^2 = 1234.519$ $P = 0.000$	$X^2 = 1185.076$ $P = 0.000$	$X^2 = 22.677$ $P = 0.000$
R ²	0.885	0.900	0.712

Notes: $Ln/Sale_{i,t}$ as the dependent variable. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6. Test result of dummy variable

Variable	Integrated data (Eq. (1))	Integrated data (Eq. (3))
$\text{LnRank_1}_{i,t-1}$	-0.852** (0.063)	-1.717*** (0.149)
$\text{LnSale_2}_{i,t-1}$	0.013** (0.025)	-0.078*** (0.019)
$\text{Discount}_{i,t-1}$	-0.958*** (0.535)	-5.245*** (0.794)
$\text{DisLnRank_1}_{i,t-1}$	0.054*** (0.100)	1.486*** (0.221)
Culture		-6.308*** (0.602)
Culture * $\text{LnRank_1}_{i,t-1}$		1.512*** (0.153)
Culture * $\text{LnSale_2}_{i,t-1}$		0.173*** (0.021)
Culture * $\text{Discount}_{i,t-1}$		4.783*** (0.904)
Culture * $\text{DisLnRank_1}_{i,t-1}$		-1.390*** (0.238)
Number of observations	22423	22423
Hausman test	$X^2 = 941.537$ $P = 0.000$	$X^2 = 302.956$ $P = 0.000$
R ²	0.817	0.774

Notes: $\text{LnSale}_{i,t}$ as the dependent variable. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6 based on Hausmann test results ($X^2 = 941.537$, $P = 0.000$). Then, according to the Hausman specification test results, we estimate a FEM of Eq. (3) for the single data set, and the results are provided in Table 6, Column 3. As suggested, product ranking still has a significant effect. Moreover, the coefficient of *Culture* is statistically significant. The coefficient of interaction term between cultural orientation and product ranking (*Culture* * $\text{LnRank_1}_{i,t-1}$) is also significant. These results indicate that there is a significant difference in the impact of product ranking on customers with different cultural orientation. The results in Table 5 have been shown that the absolute value of the coefficient on $\text{LnRank_1}_{i,t-1}$ for American consumers (0.610) was less than that for Chinese consumers (1.023 and 1.196). Thus, all above approaches suggest that information cascades are more eminent for Chinese consumers than for American consumers, supporting H4. In addition, the coefficient of interaction term between cultural orientation and price discount (*Culture* * $\text{Discount}_{i,t-1}$) is significant, and the coefficient of interaction term between product ranking, price discount and cultural orientation (*Culture* * $\text{DisLnRank_1}_{i,t-1}$) is also significant. These results indicate that the impact of price discounts on product sales is moderated by the cultural origin of consumers, both for high-ranking products and low-ranking products.

Overall, our results indicate that, except for H2, all hypotheses received support.

5.3. Robustness Check

First, one may be concerned about the potential collinearity among our model variables. Using a similar method with Lin (2014), we perform mean-subtracted centralization to all the independent variables. For ease of comparison, Columns 2, 4 and 6 of Table 7 provide the results for Columns

2, 3 and 4 in Table 5, respectively. We re-estimate Eq. (1) based on these variables for the two data sets based on Hausmann test results ($X^2 = 1234.519$, $P = 0.000$), and the FEM results are provided in Table 7, Columns 3 and 7. As shown, these results are in line with those in Table 7, Column 2 and Column 6. Next, Eq. (2) was re-estimated for the sample set of Tmall.com based on Hausmann test results ($X^2 = 1185.076$, $P = 0.000$). Table 7, Column 5 summarized the FEM results, which also similar to with those in Table 7, Column 4.

Second, the datasets used in our study were crawled from electronic commerce platforms named Tmall and eBay. So, we cannot collect the variables that do not appear on the platforms, although several variables may have an influence on online purchase behavior. Additionally, some information, such as the description of products, product pictures, videos and online reviews, may also be included in the product display pages on the Tmall and eBay platforms, however, these variables are not included in our datasets or research models. Hence, the possible concern is whether the findings will be affected by the control variables this study use. In the model construction process, Eq. (1) only includes the independent variables, while Eq. (2) includes both the independent variables and the control variables. The Column 2 of Table 7 is the result of using Eq. (1) to estimate the Tmall data, and the Column 4 of Table 7 is the result of using Eq. (2) to estimate the same data set. By comparing the results of these two columns, we can find that the estimate results of all the independent variables are similar.

In sum, above check results indicate robustness and consistency of our findings.

6. DISCUSSION AND CONTRIBUTION

This study investigates the impact of information cascades on online shopping behavior and cross-culturally compares its impact on Chinese consumers and American consumers. In addition, we also analyzed the role of information cascades in moderating the impact of price discounts on online shopping behavior.

6.1. Discussion of Findings

The results show that product ranking has a positive influence on the product sales in the online shopping market. This is in line with the forecasts of the informational cascades' studies, in which the information deduced from others' actions performed significant effect on the choice of individuals. This is also similar to Simonsohn and Ariely (2004) and Liu et al. (2016), which found the significant effect of information cascades on online purchase behavior from eBay.com and Tmall.com, respectively.

The results also suggest that information cascades moderate the impact of price discounts on online purchase behavior. However, this moderating effect is different for Chinese consumers and American consumers. For Chinese consumers, price discounts have a negative impact when purchasing higher ranking products online, but they have a positive impact when purchasing lower ranking products online. For American consumers, price discounts have no effect when purchasing high-ranking products online, but they have a positive impact when purchasing low-ranking products online.

The results also indicate that information cascades are more salient for Chinese consumers than for American consumers. Prior research has suggested that Chinese consumers mostly have the collectivist cultural orientation, while American consumers mostly have the individualistic cultural orientation (Deufel et al., 2019; Wang et al., 2019). Hence, these findings are similar to the studies of Luo et al. (2014) and Cho and Kim (2017), which find that individualistic consumers make decisions based primarily on their own information and understanding, while collectivist consumers are more likely to follow the actions of previous people.

The findings also suggest that when shopping online, the network effects have a positive and significant impact. This is consistent with the study of Liu et al. (2016), which shows that online purchase behavior is affected by network effects. Moreover, by comparing the impacts of network effects on Chinese consumers and American consumers, we unravel that network effects have a greater

Table 7. Robustness checks

Variable	Tmall data (Eq. (1))	Mean- centering for Tmall data (Eq. (1))	Tmall data (Eq. (2))	Mean- centering for Tmall data (Eq. (2))	eBay data (Eq. (1))	Mean- centering for eBay data (Eq. (1))
LnRank_1 _{<i>i,t-1</i>}	-1.023** (0.075)	-1.023** (0.075)	-1.196*** (0.074)	-1.196*** (0.074)	-0.610*** (0.024)	-0.622*** (0.023)
LnSale_2 _{<i>i,t-1</i>}	0.073* (0.050)	0.079* (0.048)	0.043** (0.016)	0.043** (0.016)	0.002* (0.023)	0.003* (0.021)
Discount _{<i>i,t-1</i>}	-1.831* (0.954)	-1.831* (0.954)	-0.527** (0.195)	-0.527** (0.195)	-0.794 (0.701)	-0.796 (0.702)
DisLnRank_1 _{<i>i,t-1</i>}	0.191** (0.180)	0.191** (0.180)	0.118*** (0.069)	0.118*** (0.069)	0.005** (0.002)	0.006** (0.002)
LnStock_1 _{<i>i,t-1</i>}			-0.075** (0.005)	-0.075** (0.005)		
LnNumber_2 _{<i>i,t-1</i>}			0.062 (0.008)	0.063 (0.006)		
LnRating_2 _{<i>i,t-1</i>}			-0.067 (0.006)	-0.067 (0.006)		
LnCollection_2 _{<i>i,t-1</i>}			0.162** (0.068)	0.162** (0.068)		
Number of observations	13925	13925	13925	13925	8498	8498
Hausman test	χ^2 =1234.519 $P=0.000$	χ^2 =1234.519 $P=0.000$	χ^2 =1185.076 $P=0.000$	χ^2 = 1185.076 $P=0.000$	χ^2 = 22.677 $P=0.000$	χ^2 = 22.677 $P=0.000$
R ²	0.885	0.885	0.900	0.900	0.712	0.712

Notes: $\ln \text{Sale}_{i,t}$ as the dependent variable. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

impact on consumers with a collectivist cultural orientation than consumers with an individualistic cultural orientation.

6.2. Theoretical Contributions

This study offers important theoretical contributions in the following ways. Firstly, this research contributes to the information cascades literature by considering the moderating role of cultural orientation. Previous studies demonstrated the moderating effects of cultural orientation from the standpoint of social influence (Hu et al., 2020; Lee and Choi, 2019; Pettifor et al., 2017). However, there is no study investigated the interaction between information cascades and cultural orientation in the context of online consumer behavior. To our best knowledge, this paper is the first to compare the effect of information cascades on online customers with different cultural orientation. Our results suggest that information cascades have a greater impact on consumers with a collectivist cultural orientation than consumers with an individualistic cultural orientation. This provides a new theoretical perspective and calls for more cross-cultural research on information cascades in the future.

Secondly, this research also contributes to marketing literature. There are conflicting results in the prior studies when investigating the effect of price discounts on online purchase behaviors (Cao et al., 2018; Dhar et al., 2007; Erdem et al., 2008; Rao & Monroe, 1989; Xu and Huang, 2014). Instead of assuming that price discounts have a uniform impact across products in prior studies, this study investigates the moderating effect of information cascades on price discounts. Our findings indicate

that when consumers shop online, price discounts have different effects on products with high rankings and products with low rankings. Moreover, our results also suggest that the interaction effect between price discounts and information is also moderated by the customers' cultural orientation. These may provide an explanation for the conflicts in some of the results that appeared in prior studies on price discounts.

Finally, this research contributes to the literature on network effects by investigating the influence of customers' cultural orientation. This provides a new research perspective to analyze the impact of network effects on consumers with different cultural orientations. Moreover, our results indicate that both network effects and information cascade effects exist in the context of online shopping, which is inconsistent with the results of the software adoption study by Duan et al. (2009). Our results suggest that the impact of network effects on online user behavior may be affected by a specific research context.

6.3. Practical Implications

This study also offers several practical implications. First, online retailers should place a high value on the role of product rankings on consumers' online shopping behavior. They should carefully study the ranking rules of major e-commerce platforms and adopt various legal methods to improve the ranking of their products. The managers of various e-commerce platforms should publicly and in detail describe the calculation methods of product rankings, and take effective measures to severely punish frauds that may exist in some enterprises.

Second, online retailers should have a deeper understanding of the moderating effects of consumers' cultural orientation on product rankings. They need to be aware that while product rankings have a significant impact on online consumer behavior, it has less impact on American consumers than on Chinese consumers. Therefore, in terms of energy and cost of improving product rankings, they can pay more in the Chinese market than in the US market.

Finally, online retailers should adopt different pricing strategies for products with different rankings in online markets in different countries. On the online market in China, they should try to offer lower price discounts or no price discounts for high-ranking products, but offer as much price discounts as low-ranking products. On the online market in United States, they should offer more discounts for low-ranking products, but they can ignore the impact of price discounts on high-ranking products.

7. LIMITATION AND FUTURE RESEARCH

This research also has some limitations. Firstly, because we only collected data on one type of product (sports shoes), whether the research findings apply to other types of products requires future research to confirm. In particular, the sample used in this study is an experience product, and future research can try to cross-culturally compare the impact of information cascades on search products.

Secondly, this study collected data on a brand created by Japan. Although Japan and China are both Asian countries, the United States and Japan have very close economic and trade relations, and the brand's sales in the United States is higher than China in 2018 (Netease, 2019). However, this may also lead to some bias in the research results. Future research can try to use the data of Chinese brands or US brands to investigate and compare the impact of information cascades on Chinese consumers and American consumers.

Thirdly, this study only compares the information cascade effect in the online market between China and the United States. Future research can try to compare the information cascade effects in more countries' online markets.

Fourthly, the results page of many products does not provide product sales and user reviews on eBay.com, which brings certain difficulties to our data collection. Although the data of the ASICS sports shoes we collected from eBay.com included product sales, it did not include user reviews.

Although our model is already very robust, the lack of data that may affect online purchase behavior may also cause some bias in our research results. Future research can try to cooperate with some companies to obtain more complete data as much as possible.

Finally, due to the difficulty of data acquisition, this study also ignores the impact of the recommendation system on online purchase behavior. Future research can attempt to investigate the impact of interactions between information cascades, word-of-mouth effects, and recommendation systems on online shopping behavior. Future research can also try to cross-culturally compare the impact of the interaction between the three on online consumer behavior in different countries.

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ENDNOTES

- ¹ https://asics.tmall.com/category.htm?spm=a1z10.1-b-s.w5001-14448682485.3.58205d44CpeGel&search=y&scene=taobao_shop
- ² http://www.ebaystores.com/asicsamerica/_i.html?rt=nc&_sacat=asicsamerica&_sasi=1&_sc=1&_sid=1336278724&_sop=100&_trksid=p4634.m14&_pgn=1

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