DISCOVERING CULTURAL DIFFERENCES
IN ONLINE CONSUMER PRODUCT REVIEWS

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ABSTRACT

In this study, we investigate whether consumers with different cultures concentrate on different product features in online consumer product reviews and show different opinions toward individual product features of the same products. To this end, we extract product features and their associated opinions (i.e., feature-opinion pairs) from online consumer reviews of the same products available at Amazon websites for U.S. and Chinese consumers. The analysis of 4,754 reviews shows that American consumers tend to focus more on usability features of products and have more negative opinions on the same product features in their online reviews than Chinese consumers. Chinese consumers, on the other hand, comment more on aesthetics of products in their reviews. These findings provide some valuable guidance for sellers and manufacturers to better customize their products and improve marketing strategies for consumers with different cultural backgrounds.

Keywords: Online consumer reviews; Text mining; Culture; Feature extraction; Opinion mining

1. Introduction

Online consumer reviews (OCRs) are generated rapidly and playing an important role in consumers' purchase decision making [Sun 2012]. OCRs enable consumers to gather other consumers' views of a product and know the product better before making informed purchase decisions. They offer great value to online retailers by helping them understand the needs and preferences of their customers, and have become a major information source for marketers and manufacturers to gather consumer feedback about product quality as well [Karimi & Wang 2017]. There has been extensive research on OCRs and their impact on sales and consumer purchasing behavior [Hu et al. 2014, Purnawirawan et al. 2015], with most focusing on the helpfulness of OCRs and the relationships between OCRs and product sales [Baek et al. 2015, Floyd et al. 2014, Korfiatis et al. 2012, Racherla & Friske 2012, Wan & Nakayama 2014, Zhu & Zhang 2010].

With the growth of economic globalization, an increasing number of products are sold internationally both in physical stores and online. Research has shown that culture is a significant factor that affects consumer behavior [Mccort & Malhotra 1993]. It is crucial for product designers and manufacturers to understand potential differences in product preferences of consumers attributable to their cultural differences so that they can better customize products, optimize their marketing strategies, and provide more relevant product information of consumers' interest accordingly [King et al. 2014]. Although several studies have probed and reported the differences in overall characteristics, such as volume, length, and overall valence, of OCRs written by consumers

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with different cultures [Fang et al. 2013, Kim 2016, Koh et al. 2010, Park & Lee 2009], little research has investigated consumer differences in product feature preferences. In this paper, product features are referred to attributes, components, and other aspects of a product, which are widely adopted in literature [e.g., Ma et al. 2013, Zhai et al. 2011a].

The textual content of OCRs may provide more details about a consumer's opinion on a product than a numeric star rating. Analysis of such content may reveal consumers' opinions and preferences of product features. In recent years, some researchers started investigating cultural differences in the textual content of OCRs. For example, Hong et al. [2016] identified general emotions in online consumer restaurant reviews on Tripadvisor.com. It was one of the early efforts to consider how cross-cultural differences could be manifested in terms of characteristics of textual online reviews beyond a simple measure of review length. They found that consumers with an individualistic culture, which emphasizes oneself more than the group, would tend to express more emotions than those with a collectivistic culture who tend to integrate oneself into a group. However, none of existing studies has examined the differences in OCRs written by consumers with different cultural backgrounds from a product feature perspective.

People with different cultures may emphasize or value different aspects of products and assess product quality in different ways. Given today's globalized businesses and economy, understanding potential differences in preferences and opinions of features of the same products by consumers with different cultural backgrounds can advance manufacturers' understanding of consumers in different markets, provide manufacturers with new insights to help them better customize their products, and improve marketing campaigns by designing more effective product advertisements. Examining consumer differences from a cultural perspective can be instrumental to product localization and developing effective strategies to improve customers' satisfaction in international markets [Zhou et al. 2016]. OCRs written by consumers with different cultures provide a natural and rich source for investigating such differences. Yet, to our best knowledge, there has been little work that explores this issue.

To address the above research gaps in the literature, we aim to address the following overarching research question in this research: Do consumers with different cultural backgrounds tend to focus on different product features in OCRs? More specifically, we analyze textual content of OCRs crawled from Amazon China and U.S. websites to examine potential differences in consumers' emphasis or preferences for product features, as well as differences in consumers' opinions on the same features of the same products.

2. Literature Review

There have been extensive studies on OCRs from a variety of perspectives in the past decade. One major stream of studies focuses on examining how review characteristics affect review helpfulness [Forman et al. 2008, Hong et al. 2017, Kuan et al. 2015, Qazi et al. 2016, Salehan & Kim 2016] and on building models for predicting the helpfulness of individual OCRs using linguistic and/or other features extracted from OCRs [Hu et al. 2017, Krishnamoorthy 2015, Mudambi & Schuff 2010, Singh et al. 2017]. Another line of research explores the economic impact of OCRs, which shows its significant role in driving product sales, pricing strategies, and customer satisfaction, etc. [Archak et al. 2011, Gao et al. 2017, Hu et al. 2008]. Some other researchers have focused on trustworthiness of OCRs [Banerjee & Chua 2019, Gavilan et al. 2018, Luca & Zervas 2016], especially automated detection of fake OCRs [Lau et al. 2011, Rout et al. 2017, Wu et al. 2017, Zhang et al. 2016].

Besides the above-mentioned research direction, there is another interesting body of research that investigates cultural differences in OCRs. Culture is one of the principal factors that can explain consumer behavior disparities [Cleveland et al. 2016]. It influences not only preferences of consumers for products, but also their intentions to purchase [Richard & Habibi 2016]. Consumer behavior across different cultures may differ because value systems differ from one culture to another. Research suggests that consumers from cultures that differ in values will differ in their reactions to foreign products, advertising, and preferred sources of information [Cleveland et al. 2016, Pornpitakpan & Francis 2000, Spiers et al. 2014]. One cultural factor that affects consumer behavior is the level of diversity and uniformity within a culture. Collectivistic cultures tend to place a strong value on uniformity [De Mooij 2010], while individualistic cultures tend to value diversity. Therefore, OCRs posted by consumers with various culture backgrounds could vary and reflect different interests of consumers. Hofstede's cultural dimensions have been one of the most widely adopted theories in cross-cultural studies. The theory has also been adopted in OCR related research, as shown in Table 1. Hofstede's national cultural dimensions include (1) power distance index (PDI); (2) individualism vs. collectivism (IDV); (3) uncertainty avoidance index (UAI); (4) masculinity vs. femininity (MAS); and (5) long-term orientation vs. short-term orientation (LTO) [Hofstede 2011].

- Power distance index (PDI): In a high power distance culture society, people are more willing to accept that people are in different social hierarchies. In a low power distance culture, the relationships among members are more democratic.
- Individualism vs. collectivism (IDV): IDV explores the "degree to which people in a society are integrated into groups" [Hofstede 2011, p11]. People in collectivistic societies usually support each other and build stronger and tighter relationships than those with individualistic cultures. Individualists emphasize oneself more than the group.

Table 1. A Summary of Previous Cross-cultural Studies on OCRs

Authors	Country	Methodology	Main Findings	Major Limitations
Koh et al. [2010]	U.S., China, Singapore	Used a survey regarding online movie reviews.	Consumers with a collectivistic culture write fewer negative reviews than those with an individualistic culture. Social norms have a greater influence on the ratings of movies in collectivistic societies than in individualistic societies.	The positive and negative reviews were analyzed by ratings. They did not examine textual content of OCRs.
Fang et al. [2013]	U.S. vs. China	Used IDV, PDI and UAI dimensions of Hofstede theory as theoretical lens.	Compared with American consumers, Chinese consumers seemed to be less engaged with OCR platforms, wrote fewer negative reviews, and cared more about negative reviews.	They treated reviews with high (or low) ratings as positive (or negative) reviews. Ignored textual content.
Zhou et al. [2016]	U.S. vs. China	Used an automatic question generation method and automatic answer extraction to find out frequent and popular aspects from OCRs collected from Amazon websites.	Consumers in China often used more euphemistic expressions in OCRs, while consumers in the U.S. used more direct expressions. American consumers focused more on product details and were more concerned about internal features of products than Chinese consumers.	Ignored infrequent and unpopular product features.
Hong et al. [2016]	52 countries	Utilized LIWC, a text analysis software, for identifying sentiments and emotions in textual content of OCRs.	Consumers with an individualistic culture would be more likely to express emotions and deviate from prior opinions expressed in reviews than those from a collectivistic culture.	Did not discuss features of products in OCRs. Only used data from U.S. cities.
Kim et al. [2016]	U.S. vs. South Korea	(1) Collected reviews in Seoul on Booking.com. (2) Applied a matching method to explain cultural differences.	Korean consumers tend to give lower ratings than American consumers. The impact of positive and negative events was stronger on Korean customers than on U.S. customers, resulting in a lower level of heterogeneity in OCRs of U.S. customers.	Only used OCRs of hotels in Seoul. Only considered numeric information (e.g., ratings) of OCRs.
Zhu et al. [2017]	U.S. vs. China	Collected and analyzed OCRs from Amazon.com and Amazon.cn based on IDV and PDI dimensions of Hofstede theory.	Proposed 10 dimensions (e.g., seller trustworthiness, logistic quality, service quality, product functionality, price) of textual content of OCRs.	Did not consider review valence. Did not examine opinions associated with product features.

- Uncertainty avoidance index (UAI): UAI indicates people's tolerance for ambiguity. In a high uncertainty avoidance society, people are more uncomfortable about unknown and surprising situations than those in a low uncertainty avoidance culture. People with a low uncertainty avoidance culture are more willing to embrace changes.
- Masculinity vs. femininity (MAS): The Masculinity side of this dimension represents a preference in society for achievement, heroism, assertiveness, and material rewards for success. People with a higher masculinity culture have strong egos, and the society is more competitive. Femininity stands for a preference for cooperation, modesty, caring for the weak, and quality of life. A culture with higher femininity refers to a society that is more consensus/relationship-oriented and focuses more on quality of life.
- Long-term orientation vs. short-term orientation (LTO): Long-Term Orientation stands for fostering in a society of pragmatic virtues oriented to future rewards, in particular perseverance, thrift, and adapting to

changing circumstances. Short-Term Orientation stands for fostering in a society of virtues related to the past and the present, such as respect for tradition and stability, preservation of face, and fulfilling social obligations.

There are a limited number of studies that have examined OCRs from a cross-cultural perspective. For instance, Koh et al. [2010] compared the OCR posting behaviors of Chinese and American reviewers and examined how cultural elements may influence the attitudes and intentions of consumers in the hybrid culture of Singapore. They found that consumers from collectivistic societies would tend to keep harmony and write fewer negative reviews than those from individualistic societies. Table 1 presents a summary of some cross-cultural studies on OCRs.

In summary, up to date, there are only a very small number of studies that have investigated OCRs from a culture difference perspective. Some of them only analyzed product ratings instead of textual content of OCRs. Even though a couple of studies did look into OCR content, they mainly focused on the overall sentiments or expressions of OCRs. None of the studies has investigated differences in textual content of OCRs at a level of individual product features. Prior research has suggested that OCR analysis at a product feature level (e.g., aspect-oriented sentiment analysis) would provide more detailed insights about consumer preferences, which can be beneficial to product innovation and improvement [Broß 2013, Yan et al. 2015]. In addition, prior studies analyzed OCRs of products in limited product categories, which makes the generality of conclusions uncertain. Motivated to address the above limitations, this research is intended to provide novel insights into differences in consumer preferences of specific types of product features by analyzing and comparing textual content of OCRs of consumers with different cultures at a product feature level.

3. Hypothesis Development

Prior research has suggested that OCR posting behavior and general characteristics of OCRs may be influenced by certain dimensions of Hofstede's cultural theory, such as individualism-collectivism and uncertainty avoidance [Fang et al. 2013, Zhu et al. 2017], and national culture has influence on how people use products [Honold 2000]. Thus, we expect that national culture affects the way that people evaluate products, which could be reflected in the content of OCRs.

In this study, we use the Hofstede's cultural dimensions as the theoretical lens to investigate whether there are significant differences in product features and opinions commented in OCRs between American and Chinese consumers. We selected OCRs of Chinese and American consumers because of two main reasons. First, according to Hofstede's cultural dimensions, Chinese and American cultures are considerably different, with the former being collectivism and having lower uncertainty avoidance but higher power distance, while the latter being individualism and having higher uncertainty avoidance but lower power distance, which provides a desirable cultural contrast. The scores of cultural dimensions in U.S. and China are shown in Table 2[1]. Second, China and U.S. have two largest e-commerce markets in the world. The number of Chinese online shoppers reached 610 million by the end of December 2018 [CNNIC 2019], while 220.6 million Americans shopped online in 2018[2].

Table 2. Cultural Dimension Scores of China and U.S.

Country	Individualism	Uncertainty Avoidance	Long-term Orientation	Power Distance	Masculinity
China	20	30	87	80	66
U.S.	91	46	26	40	62

Given the focus of our study, we adopted the IDV and UAI dimensions as the theoretical underpinning. We exclude other three dimensions because the masculinity and femininity (MAS) dimension focuses on cooperation and modesty in a feminine society and emphasizes heroism, performance and achievement in a masculine society, which has no direct relationship with OCRs. In addition, U.S. and China are very similar in this dimension (China scored 66 and U.S. scored 62, as shown in Table 2), so that it is not suitable to explain the differences in OCRs between American and Chinese consumers. Similarly, the long-term orientation (LTO) culture suggests that people are comfortable with adaption to the changing environment while short-term orientation culture values steadiness and stability, which is not closely related to the behavior of OCRs either. The PDI dimension is often used to explain potential behavioral differences among people caused by disparity of social status, which is not applicable to the context of this study because social hierarchies do not exist in online consumer review platforms due to their open and anonymity nature.

Emotions bear greater interpersonal meanings in individualistic cultures than in collectivistic cultures [Suh et al. 1998]. In the former, personal feelings reaffirm the higher importance of individuals compared to social relationships. Collectivistic cultures, however, focus more on social relationships. Collectivists value

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[1] https://www.hofstede-insights.com/product/compare-countries/

[2] https://www.statista.com/statistics/183755/number-of-us-internet-shoppers-since-2009/

interdependence and tend to place group interests above personal interest [Hofstede 2001]. Therefore, expression of personal feelings in collectivistic cultures is relatively less important and may be somewhat refrained [Matsumoto et al. 2008]. In individualistic cultures, people are more likely to express personal thoughts. They value individual emotion expression [Hofstede 2001] and are unlikely to hide their opinions even if they have different opinions from others. Accordingly, people from individualistic cultures (e.g., Americans) would be more likely to express their feelings and be more talkative and extroverted than people from collectivistic cultures (e.g., Chinese) [Mccrae & Terracciano 2005]. It is suggested that individualism would have a significant positive correlation with extraversion [Arpaci et al. 2018].

In general, OCRs typically contain seller-related comments (i.e., seller trustworthiness, logistic quality, and service quality), product-related comments (i.e., product functionality, price, product quality, and product aesthetics), and/or consumer-related comments (i.e., emotional attitudes, recommendation expressions, and attitudinal loyalty) [Zhu et al. 2017]. The product-related content is arguably the most important element of OCRs. According to the above cultural differences, because individualists are more open and extroverted than collectivists, we expect that people with individualistic cultures would express more emotions, feelings, or opinions than those with collectivistic cultures not only in their daily life, but also on the review platform of e-commerce websites. As a result, individualists are more likely to express more opinions on products than collectivists and focus more on product features than the latter. Additionally, it is indicated that consumers with an individualistic culture may provide a larger number and longer online reviews than those with a collectivistic culture [Fang et al. 2013]. Therefore, it is reasonable to predict that American consumers (with an individualistic culture) are likely to focus more on product features than Chinese consumers (with a collectivistic culture). Thus, we propose the following hypothesis:

H1: *American consumers tend to focus more on product features in OCRs than Chinese consumers.*

Sharing opinions is the vehicle for people to convey their emotions to others [Salehan & Kim 2016]. OCRs provide a channel for people to express their opinions on products [Felbermayr & Nanopoulos 2016]. Different people may have different preferences and expectations, so they may have different opinions toward the same products. Consumers' feelings about a product can be influenced by culture [Gi Park et al. 2014]. In collectivistic cultures, people value their identity in their social system. They emphasize conformity, empathy, and dependence because they tend to behave nicely and allow people to blend into a social group [Merkin 2015]. Therefore, collectivists have a stronger desire for keeping harmony and being less confrontational or hostile than individualists [Merkin 2015]. They tend not to express their opinions, especially those negative ones, in public environments [Butler et al. 2007], and try to maintain relations with all other people with whom they interact and avoid hurting others' feelings. Following this logic, they are expected to express fewer negative opinions on product features in OCRs. In contrast, people with an individualistic culture tend to care more about their self-esteem and being unique [Liu & McClure 2001], thus more likely to share their emotions, even when they are negative, with others openly and publicly [Hong et al. 2016]. For example, Americans (high IDV) usually do not suppress their emotions but rather openly express what they feel, whereas East Asians (low IDV) are usually willing to adjust their behavior according to others and suppress their emotions [Nam et al. 2017]. Therefore, it is reasonable to predict that American consumers are likely to share more negative opinions on product features than Chinese consumers. Thus, we propose Hypothesis 2 as follows:

H2: *American consumers tend to share more negative opinions on product features in OCRs than Chinese consumers.*

Usability and aesthetics are two very important aspects that customers consider when purchasing a product. Usability is one of the major determinants of user attitude and intention to buy a product [Lee & Koubek 2010]. It can be defined as the extent to which a product can be used by users to achieve goals with effectiveness, efficiency, and satisfaction in a specific context of use [ISO 1998]. A few prior studies differentiated usability features from utility features [Lacka & Chong 2016], but many others did not (e.g., [Lee & Koubek 2010]). For example, Lee & Koubek [2010] defined perceived usability as a user's subjective perceptions and judgments of usability attributes of an entity, including perceived usefulness, ease-of-use, and also utility attributes (e.g., functionality). Therefore, we also did not differentiate usability and utility in this research.

It is argued that perceived usability can be affected by culture [Oyibo & Vassileva 2016, Shin 2012]. People from different cultures have different perceptions and preferences of usability. Usability attributes are not assessed and rated equally by consumers from different cultures [Seidman 2013]. People with a higher uncertainty avoidance culture tend to be more uncomfortable with ambiguous, unknown, and surprising situations [Hofstede 2011]. To reduce uncertainty of purchasing products online, we expect that they tend to gather more relevant product information, including product usefulness, ease-of-use, and functional features (e.g., usability information). Accordingly, people with a high uncertainty avoidance culture are expected to comment more on or be concerned about the usability of a product. As a result, we predict that American consumers (with higher uncertainty avoidance) may comment more on usability features of a product in OCRs than Chinese consumers (with lower uncertainty avoidance). Thus, we propose Hypothesis 3 as follows:

H3: *American consumers tend to focus more on product usability in OCRs than Chinese consumers.*

Product aesthetics refer to the perceived appearance and beauty of a product [Bloch 2011]. People's cultural backgrounds are also found influential to perceived aesthetics [Oyibo & Vassileva 2016, Shin 2012]. In Reinecke and Bernstein's study [2011], they suggested that what users perceive as beautiful would strongly depend on their cultural background. For example, people from different cultures have different attitudes toward aesthetics when interacting with user interfaces [Reinecke & Bernstein 2013]. In the Chinese culture, product appearance or design appeal would affect one's mianzi (i.e., face) [Filieri & Lin 2017]. Mianzi is defined as "prestige and honor that accrues to a person as a result of successes and/or ostentatious behavior before others [Li et al. 2007, p49]." It is the self-image that people try to maintain in front of others [Hwang et al. 2003]. In collectivistic countries (e.g., China), people care more about their mianzi than individualists because mianzi has functions and social significance to keep group harmony [Kam & Bond 2008, Zane & Yeh 2002]. People can gain mianzi through products with fashionable and good-looking designs [Filieri & Lin 2017]. Therefore, we predict that Chinese consumers (collectivistic culture) are likely to emphasize more on product aesthetics in OCRs than American consumers (individualistic culture), as posited by hypothesis H4:

H4: *Chinese consumers tend to focus more on product aesthetics in OCRs than American consumers.*

4. Research Methodology

4.1 Data Collection

To avoid potential confounding effect of different online retailers, we chose OCRs of the same products from the Chinese and U.S. websites of Amazon (i.e., Amazon.com and Amazon.cn), which have identical OCR platforms except the language used, as shown in Figures 1 and 2.
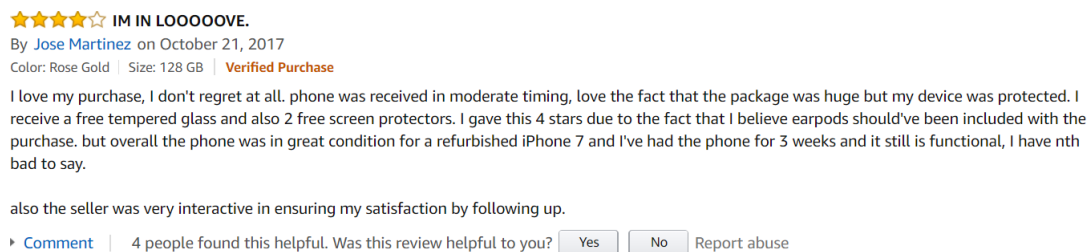

Figure 1. A Screenshot of an OCR at Amazon.com

Figure 2. A Screenshot of an OCR at Amazon.cn
(The content shown in rectangles is the corresponding English translation)

In this study, we considered several products sold on both Amazon.com and Amazon.cn that had already received at least 100 online consumer reviews. According to Nelson's studies [Nelson 1970, 1974], products can be categorized into search goods and experience goods. Search goods, such as cloth and furniture, are those that consumers are able to collect information regarding product quality before purchasing. Experience goods, on the other hand, are products that need sampling or actual experience in order to assess product quality. Although the Internet makes all product attributes easy to search and thus makes the distinction between search and experience goods subtle [Huang et al. 2009], there are still differences between these two product types [Viglia et al. 2014] as experience goods can still be better assessed through actual experience. By considering both types, we collected OCRs of eight products, including Canon EOS 6D digital camera, iPhone 7, Logitech M185 mouse, Elizabeth Arden green tea scent perfume, Garmin Vivoactive HR smartwatch, Kindle Paperwhite e-reader, Puma Suede Classic shoes and Ferrero chocolate, among which perfume, shoes, and chocolate are experience goods and the rest are search goods. Cameras were considered as experience goods in the past [Nelson 1974, Huang et al. 2009]. Nowadays cameras are digital products that are easily searchable online. Like many other digital products such as mobile phones and tablets, cameras are now viewed as search goods rather than experience goods (e.g.,

[Mudambi & Schuff 2010, Roy et al. 2017, Yan et al. 2015]). The descriptive statistics of the initially collected 21,895 OCRs of the eight products are presented in Table 3.

Table 3. The Numbers of Collected OCRs from the Two Amazon Websites

	Canon digital camera	iPhone 7	Logitech M185 mouse	Elizabeth perfume	Garmin smart-watch	Kindle e-reader	Puma shoes	Ferrero chocolate	Total
Amazon.com	770	598	1,800	360	2,007	9,779	1,638	431	17,383
Amazon.cn	215	426	500	360	117	1,990	536	368	4,512

Because the numbers of OCRs of the same products on the two Amazon platforms differ significantly for 7 out of the 8 selected products (assuming there are m reviews crawled from the OCR platform A and n reviews of the same product crawled from the platform B, and $m>n$), in order to avoid the potential effect of OCR size on analysis results, we randomly selected n reviews from the original m reviews of a product so that there would be equal numbers of reviews of the same products from both Amazon platforms. In the end, our dataset for analysis consisted of 4,754 OCRs, as shown in Table 4. We then extracted product rating and content from each selected review.

Table 4. Descriptive Statistics of Selected OCRs

		Camera	iPhone	Mouse	Perfume	Smart-watch	E-reader	Shoes	Chocolate
OCR Posting Time period		2012.12-2016.12	2016.9-2017.12	2014.5-2017.9	2013.1-2018.1	2016.2-2017.12	2017.3-2017.9	2017.1-2019.1	2015.1-2019.1
Amazon.com	# of selected OCRs	215	426	482	280	110	400	310	154
	# of positive ratings	203	300	399	245	64	346	254	139
	# of negative ratings	6	111	57	21	33	29	29	11
	# of neutral ratings	6	15	26	14	13	25	27	4
Amazon.cn	# of selected OCRs	215	426	482	280	110	400	310	154
	# of positive ratings	201	318	390	215	92	321	307	126
	# of negative ratings	7	73	56	28	11	50	20	18
	# of neutral ratings	7	35	36	37	7	29	12	10

Note: positive ratings refer to 4- and 5-star ratings; negative ratings refer to 1- and 2-star ratings; neutral ratings refer to the 3-star rating

4.2 Feature and Opinion Extraction

To test the hypotheses, we first extracted product features and associated opinions (i.e., feature-opinion pairs) from the unstructured Chinese and English OCRs (Figure 3). We removed useless characters from the OCRs, including special symbols such as "*" and "#". Then, we performed word tokenization and Part-of-Speech (PoS) tagging using tools including Language Technology Platform (LTP, http://ltp.ai) for Chinese sentence segmentation, Natural Language Toolkit (NLTK, http://www.nltk.org/), and Stanford Natural Language Processing (NLP, http://nlp.stanford.edu). The English and Chinese OCRs were processed in the same way.

Next, we conducted a dependency analysis to discover syntactic relations between words in sentences by using the Stanford Parser for both English and Chinese corpora. The procedures of analysis of Chinese and English corpora were identical. There are two types of dependency relations between product features and opinion words [Kang & Zhou 2016, Qiu et al. 2011]. The first one is direct dependency, which means that one word depends on another without any other words in their dependency path. It shows a modification relationship between words, or both words depend on the third word directly. The second one is indirect dependency, which suggests that one word indirectly depends on another word through some additional words, or both depend on the third word through other words. Parsing indirect relations is error-prone for online corpora [Zhang et al. 2010]. Thus, we only focused on direct relations while extracting opinion words and feature candidates in our study. After parsing, the relations between features and opinion words were identified automatically. Given that a feature term is either a noun or a noun phrase, and a consumer's opinions are often reflected by adjectives used in writing [Eirinaki et al. 2012, Wei et al. 2010], we focused on nouns, noun phrases, and adjectives (including JJ (adjectives), JJR (comparative adjectives), and JJS (superlative adjectives)) in textual content of the review corpus. It is also suggested that an adjective is more likely to be an opinion term if it modifies product features [Yan et al. 2015]. We did not consider
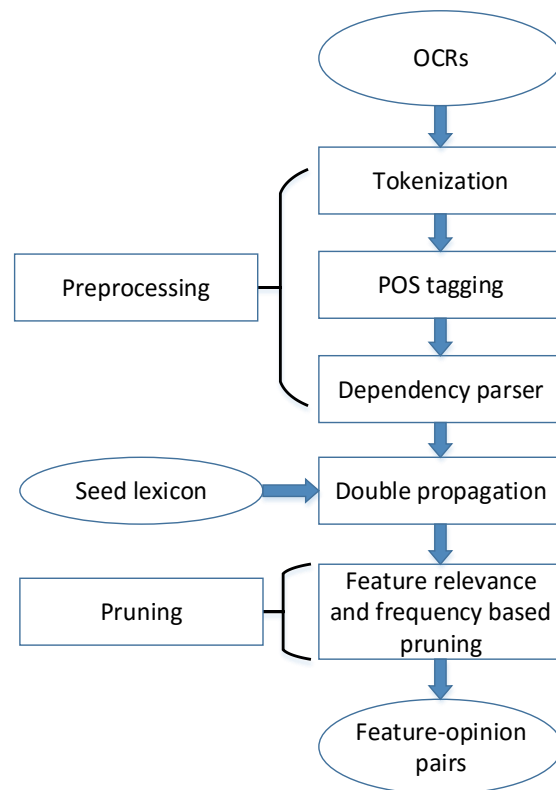
Figure 3. The Procedure of Feature and Opinion Extraction

adverbs because they usually modify adjectives and verbs instead of nouns (e.g., product features), meaning that adverbs do not have direct relationships with product features. Figures 4 and 5 show an example of direct dependency in an English sentence and a Chinese sentence.

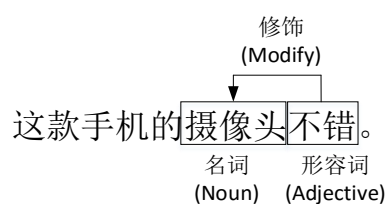Figure 4. An Example of Direct Dependency in An English Sentence

Figure 5. An Example of Direct Dependency in A Chinese Sentence

We applied the Double Propagation (DP) algorithm [Qiu et al. 2009], a method that extracts opinion words and product features iteratively through propagation using their dependency relations, to extract feature-opinion pairs for the following reasons: (1) An advantage of DP is that it is an unsupervised and domain-independent algorithm [Zhang et al. 2010], thus it does not require any additional resources except an initial opinion lexicon [Qiu et al. 2011]; (2) prior research has shown that DP performs extraction of features and opinion terms better than many other methods such as conditional random field (CRF) and association rule mining (ARF) [Kang & Zhou 2016]; and (3) DP is not only applicable to English corpora [Qiu et al. 2009, Qiu et al. 2011, Zhang et al. 2010], but also proven to be well suited for Chinese corpora [Zhai et al. 2011b].

In DP, a group of seed opinion words are used to bootstrap the propagation. In our research, we chose an English opinion lexicon [Hu & Liu 2004] and a Chinese opinion lexicon from HowNet (http://www.keenage.com/html/e_index.html) as our seed opinion lexicons. There are four tasks during the propagation: (1) extracting features through opinion words; (2) extracting features through the extracted features; (3) extracting opinion words through the extracted features; and (4) extracting opinion words through both the

given and the extracted opinion words [Qiu et al. 2009]. We adopted the specific rules proposed by Qiu et al. [2009] while completing the above four tasks. Here is an example. In the sentence "*The phone has an excellent camera*", "*excellent*" was known as an opinion word because it existed in the seed opinion lexicon, and then it was used to extract the product feature "*camera*" through their dependency relation (i.e., an adjective modifies a noun). Next, in another sentence "*The camera is awesome!*", "*awesome*" was extracted through its dependency relation with the extracted product feature "*camera*". After that, we could use "*awesome*" to extract other associated features. Newly extracted opinion words and feature terms would be used to extract more opinion words and features iteratively by following such rules. Similarly, Chinese sentences follow the same propagation rules. The process was continued until no additional opinion words and new features could be added. Note that sometimes there are negation words (e.g., no, not, hardly) before opinion words, which would change the sentiment to a totally opposite direction. Therefore, we also examined whether negation words appeared before opinion words for a more accurate analysis.

Finally, because not all the extracted nouns or noun phrases were actual product features, we had to filter the candidate feature set. Here are some steps we followed for selecting final feature-opinion pairs. First, we performed feature ranking to remove unrelated or less related terms automatically. The basic idea is to rank the extracted feature candidates by feature importance. It is suggested that two major factors affect feature importance, namely feature relevance and feature frequency [Zhang et al. 2010]. We applied the Hyperlink-induced topic search (HITS) algorithm [Kleinberg 1999] to compute feature relevance for ranking, and then removed low-relevancy features. Second, the occurrence frequency of all the candidate features was calculated and those with a very low occurrence frequency were removed. Third, we also manually removed some feature candidate terms that were not actual product features because the automatically generated results were not always 100% accurate. In the end, we also checked the extracted opinion words manually and removed incorrect ones.

To analyze consumers' sentiment polarity toward specific product features, we performed sentiment analysis using TextBolb and SnowNLP, which are Python libraries for processing English and Chinese corpora, respectively. We calculated sentiment scores of individual feature-opinion pairs. If the sentiment score associated with a product feature was larger or smaller than 0, then we considered the opinion of this product feature in the current review sentence as positive or negative, respectively. Otherwise, we viewed it as neutral.

5. Results

Every product has many features, and each product feature may have multiple associated opinion words in OCRs. We extracted a total of 1,933 feature-opinion pairs from the OCR dataset, including 1,545 from OCRs on Amazon.com and 388 from OCRs on Amazon.cn, respectively. Table 5 shows the top 3 most commented features in OCRs. Results show that consumers on Amazon.com focused on different features of the same products from those on Amazon.cn. Only five product features overlap, including screen of Kindle e-reader, quality/image quality of Canon digital camera, scent and lasting time of Elizabeth Arden perfume, and size of Puma shoes.

We performed independent two-sample t-tests to examine if there were significant differences in commented product features and opinions in OCRs between American and Chinese consumers. Independent sample t-tests have been widely used to examine differences in online review content [Fang et al. 2013, Fong & Burton 2008, Zhu et al. 2017]. The results are shown in Table 6. The mean of features denotes the average number of times that each product feature has been commented by associated opinion words. The average number is calculated at a whole dataset level rather than an individual OCR level. Similarly, the mean of negative opinions represents the average number of negative opinion words associated with each product feature in the OCRs.

The result shows that the average number of product features commented in OCRs on Amazon.com (mean=9.061) is much larger than that on Amazon.cn (mean=4.360, *P*<0.001). Similarly, the average number of negative opinions on product features expressed in OCRs on Amazon.com is larger than that on Amazon.cn (*P*<0.001). Therefore, the first and second hypotheses are supported.

To test hypotheses H3 and H4, we need to first identify usability features and aesthetics features of the selected products. According to the earlier definitions of usability and aesthetics, we manually identified/labelled them in the selected OCRs. For example, the usability features of a Kindle Paperwhite e-reader in American OCRs are screen, light, lighting, backlight, weight, battery, size, etc., and the aesthetics feature is color. It is similar with the Chinese counterpart. We then counted the numbers of usability and aesthetics features of each selected product. The average number of usability features (mean=9.752) commented in reviews on Amazon.com is larger than that on Amazon.cn (mean=4.563, P<0.001). In contrast, the average number of aesthetics features (mean=2) commented in reviews on the former OCR platform is much smaller than the number on the latter (mean=4.429, P<0.05), indicating that consumers on Amazon.com focus more on usability features while consumers on Amazon.cn focus more on aesthetics features in OCRs. Thus, the third and fourth hypotheses are also supported.

To further examine whether there are any differences in the above characteristics of OCRs between search goods and experience goods, we performed independent sample t-tests on those two types of products separately. The results shown in Tables 7 and 8 indicate that there are significant and consistent differences in commented product features and negative opinions toward features between Amazon.com and Amazon.cn in search goods.

Table 5. The Top 3 Most Commented Features in OCRs

Products	Amazon.com		Amazon.cn	
	Features	**# of opinion words on features**	**Features**	**# of opinion words on features**
iPhone 7	camera	28	声音 (sound)	12
	battery	24	屏幕 (screen)	10
	headphone	17	包装 (package)	9
Garmin smartwatch	apps, app	24	功能 (function)	7
	screen	10	设计 (design)	4
	monitor	7	表盘 (dial plate)	3
Kindle e-reader	screen	16	屏幕 (screen)	13
	light	12	质感 (texture)	3
	brightness	4	操作(operation)	2
Logitech mouse	battery	21	手感 (touching feeling)	5
	price	11	反应 (response)	4
	size	6	声音 (sound)	4
Canon digital camera	quality	50	包装 (package)	10
	sensor	42	画质 (image quality)	8
	light	41	照片 (picture)	8
Elizabeth Arden perfume	scent, fragrance	57	味道，香味，香气 (scent)	36
	lasting time	6	留香时间 (lasting time)	7
	bottle	6	价格 (price)	4
Puma shoes	size	7	尺寸，大小 (size)	22
	lace	6	质量 (quality)	7
	color	6	后跟 (heel)	3
Ferrero chocolate	chocolate	10	包装盒，盒子 (package)	8
	hazelnut	6	口感 (taste)	3
	price	5	味道 (flavor)	2

Table 6. Results of Hypotheses Testing

	U.S.		China		P Value (t value)	Hypothesis	Result
	Mean	Std. Deviation	Mean	Std. Deviation			
Features	9.061	9.6330	4.360	4.513	0.000 (5.274)	H1	Supported
Negative opinions	1.720	2.100	0.820	0.716	0.000 (4.976)	H2	Supported
Usability features	9.752	9.863	4.563	5.108	0.000 (4.862)	H3	Supported
Aesthetics features	2.000	2.000	4.429	2.652	0.011 (-2.736)	H4	Supported

Table 7. T-test Results of Search Goods

	U.S.		China		P Value (t value)
	Mean	Std. Deviation	Mean	Std. Deviation	
Features	9.518	9.562	4.015	2.295	0.000 (6.459)
Negative opinions	1.844	2.116	0.912	0.707	0.000 (4.715)
Usability features	9.860	9.527	4.039	2.306	0.000 (6.297)
Aesthetics features	1.333	1.658	4.889	2.713	0.004 (-3.355)

Table 8. T-test Results of Experience Goods

	U.S.		China		P Value (t value)
	Mean	Std. Deviation	Mean	Std. Deviation	
Features	6.261	9.808	5.476	8.382	0.778 (0.284)
Negative opinions	0.957	1.870	0.524	0.680	0.323 (1.001)
Usability features	8.667	13.262	6.615	10.445	0.670 (0.431)
Aesthetics features	3.200	2.168	3.600	2.608	0.799 (-0.264)

The result of experience goods is not the same as search goods. As shown in Table 8, the differences in focused product features, negative opinions, usability features, and aesthetics features of OCRs of experience goods between Amazon.com and Amazon.cn consumers are all statistically insignificant (P>0.05). The reason

why there are only significant differences in search goods but not in experience goods may be as follows: although they buy both search and experience goods online and post reviews of both types of products, consumers have different information requirements regarding them [Mudambi & Schuff 2010]. Without sampling or purchasing search goods, consumers can still easily acquire information about product features from a product's online description or from other consumers' reviews. However, consumers may still need to purchase or try out an experience good before writing an OCR. Thus, it is more difficult to evaluate the features of an experience good than a search good [Huang et al. 2009]. As a result, people evaluate and focus on relatively fewer features of experience goods than search goods regardless of their cultural backgrounds, which might also reduce the differences in OCRs between Chinese consumers and American consumers. Therefore, the above-mentioned differences in experience goods are insignificant.

Exploring potential differences in consumers' sentiments toward individual features of same products is also one of our research goals. To this end, we calculated and compared consumers' sentiment scores associated with product features on Amazon.com vs. those on Amazon.cn. For each identified feature-opinion pair, the sentiment score was +1, -1, or 0 when the opinion word was positive, negative, or neutral, respectively. Consumers on Amazon.com generally favored the scent of Elizabeth Arden perfume, the picture quality, the lens, the quality and body of Canon digital camera, the apps of Garmin smartwatch, the battery and camera of iPhone 7, the light and screen of Kindle e-reader, the price of Logitech mouse, the quality and color of Puma shoes and the hazelnut of Ferrero chocolate, because those features received relatively high positive sentiment scores. However, consumers' aggregated sentiment scores on Amazon.com toward the battery of Canon digital camera, the screen and band of Garmin smartwatch, and the quality of Kindle e-reader were negative. The OCRs on Amazon.cn show that the scent of Elizabeth Arden perfume, the performance, the function and Wi-Fi of Canon digital camera, the function of Garmin smartwatch, the screen and sound of iPhone 7, the screen of Kindle e-reader, the battery of Logitech mouse, and the size and quality of Puma shoes received positive aggregated sentiment scores, but the lasting time of Elizabeth Arden perfume, the price and battery of Canon digital camera, the band of Garmin smartwatch, the quality, the price, and headphone of iPhone 7, the battery of Kindle e-reader, the light and quality of Logitech mouse, and the shoe-pad of Puma shoes received negative overall sentiment scores. These results indicate that American consumers are different from Chinese consumers in their sentiments toward the same product features.

6. Discussion

In this research, we investigated cross-cultural differences in the textual content of online consumer product reviews on the Amazon websites for U.S. and Chinese consumers. We proposed a set of hypotheses based on Hofstede's cross-cultural dimensions. We hypothesize that consumers with different degrees of individualism/collectivism and uncertainty avoidance will differ in terms of focused product features and their opinions on product features commented in OCRs. We particularly focused on usability and aesthetics features of eight different products. We extracted feature-opinion pairs from OCRs and conducted a comparative study between OCRs of the same products on Amazon.com and Amazon.cn.

There are several major findings of this research. In the context of OCRs, American consumers on Amazon.com tend to focus more on product features and share more negative opinions toward them than Chinese consumers on Amazon.cn. American consumers seem more likely to focus on product usability features yet less on product aesthetics features in contrast to Chinese consumers. In addition, our study found that above-mentioned significant differences existed in search goods but not in experience goods.

This study provides multifold research contributions. First, prior cross-cultural studies mainly focused on general characteristics of OCRs [Fang et al. 2013, Gao et al. 2018, Kim 2016, Koh et al. 2010], but rarely studied textual content of OCRs to explore consumers' preferences on product features. We used the two dimensions of Hofstede's culture theory as a theoretical lens of this study and found that consumers from two distinct cultural backgrounds have different focus on features of the same products in OCRs. Second, to the best of our knowledge, none of the existing cross-cultural literature has examined consumers' different sentiment inclinations toward the same product features by extracting feature-opinion pairs from OCRs. We explored this issue in this research, and the results indicate that consumers with different cultures may perceive the features of the same products differently. Third, unlike exploring the sentiment of consumers toward a product at a review level as prior cross-cultural studies did [Fang et al. 2013, Koh et al. 2010], we specifically focused on the opinions of individual product features, which enables us to achieve a better understanding of consumers' preferences from a cross-cultural perspective. We suggest future research to consider adopting such a product-feature level analysis and comparison of OCRs so as to gain more accurate and in-depth insights about market needs and consumer preferences in different countries with variant cultures.

This study also provides some important practical implications. Our findings clearly suggest that product manufacturers should understand unique preferences and needs of certain products and their features desired by consumers with different cultures so that they can better customize or improve their products to suit the needs of different markets. Such an understanding can also enable marketing companies to develop more effective marketing campaigns to advertise products effectively in countries with different countries. For example, it may

be better to emphasize more on aesthetics features of a product in advertisements in countries like China but to highlight more usability features of a product in a country like U.S. In addition, online retailers can also customize their websites in countries with different cultures by providing OCR summaries [Kangale et al. 2016] based on consumer preferred product features to help consumers reduce product quality and product fit uncertainty quickly and easily.

There are limitations of this study that provide future research opportunities. First, we only used data collected from two OCR platforms in two countries. Although these two countries are very different in terms of Hofstede's cultural dimensions and have been frequently adopted in prior cross-cultural studies [Fang et al. 2013, Koh et al. 2010, Zhou et al. 2016, Zhu et al. 2017], there are many other countries with diverse cultures that can be studied to further validate the findings. Second, we assumed that all the reviews that we collected from Amazon.com (or Amazon.cn) were written by consumers with high (or low) individualism and uncertainty avoidance like previous studies [Fang et al. 2013, Hong et al. 2016, Zhu et al. 2017], which may or may not always be the case. It would be worthy to explore how to verify the cultural dimensions of the consumers who wrote original reviews in future research. Third, although some sources reported gender percentages of online consumers who post OCRs (e.g., 77% of female and 64% of male online consumers in the U.S. post OCRs[3]), we could not compare the differences in OCRs between male and female consumers because it is very difficult, if not entirely impossible, to know the gender of reviewers who wrote individual OCRs analyzed in this study due to the anonymous nature of OCRs. However, it could be an interesting issue to explore through natural or online field experiments in the future.

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