Electron Commer Res
DOI 10.1007/s10660-017-9266-7

Effects of membership tier on user content generation behaviors: evidence from online reviews

Dongpu Fu[1] · Yili Hong[2] · Kanliang Wang[3] · Weiguo Fan[4]

Abstract Online shopping websites typically classify customers into different membership tiers in their customer relationship management systems. This study investigates the effects of membership tiers on user content generation behaviors in the context of an electronic commerce marketplace that has a membership tier program and an online review system. Grounded in theories related to status, our study hypothesizes the effects of membership tiers on user content generation behaviors as well as the helpfulness of the content they generated in the context of online reviews. We collected online data from a world-leading shopping website. The results from our empirical analyses indicate that membership tier has a positive effect on review rating and review delay, whereas it has a negative effect on review

✉ Kanliang Wang
klwang@ruc.edu.cn

Dongpu Fu
fudongpu@cueb.edu.cn

Yili Hong
hong@asu.edu

Weiguo Fan
wfan@vt.edu

1 School of Information, Capital University of Economics and Business, 121 Zhangjialukou, Huaxiang Fengtai District, Beijing 100070, People's Republic of China

2 Department of Information Systems, W.P. Carey School of Business, Arizona State University, Main Campus, PO BOX 874606, Tempe, AZ 85287-4606, USA

3 Department of Management Science and Engineering, School of Business, Renmin University of China, No. 59 Zhongguancun Street, Haidian District, Beijing 100872, People's Republic of China

4 Department of Accounting and Information Systems, Pamplin College of Business, Virginia Polytechnic Institute and State University, Pamplin Hall, Suite 3007, Virginia Tech 880 West Campus Drive, Blacksburg, VA 24061, USA

Published online: 18 July 2017

depth. Additionally, we tested mediation effects of review rating, depth and delay between membership tiers and review helpfulness, and found that membership tier negatively affected review helpfulness indirectly. Interestingly, reviews posted by high-status customers are perceived as more helpful than those of others when we controlled for review characteristics. This study contributes to research on online product reviews and customer relationship management.

Keywords User content generation · Online reviews · Membership tier · Status

1 Introduction

Online shopping websites typically implement customer relationship management systems to enhance customer engagement. Conventionally, a membership tier program classifies and rewards customers with different levels of membership status [1–3] with differentiated levels of service. Users primarily engage with websites in two ways, namely, by purchasing products and by generating online reviews. Online reviews are important user-generated contents that contain rich information on product attributes and qualities as experienced by customers. There is an agreement among researchers that online product reviews reduce product quality uncertainty [5], alleviate the perception of online shopping risk, and help consumers make purchasing decisions [6–9]. Moreover, online reviews affect sales of shopping sites [10, 11]. Therefore, online shopping sites usually pay special attention to online reviews generated by users [12]. As a direct outcomes of user engagement, product ratings and reviews represent the reputation of sellers or products and influence sales [10, 12]. Furthermore, online review content quality may help consumers' purchase decision-making and affect actual consumer shopping behaviors [13–15]. In summary, online reviews are essential for both sellers and consumers. Due to the paramount importance, various aspects of user content generation behaviors (i.e., review rating, delay, and depth) are the types of engagement that this study focuses on.

In modern society and in hierarchical organizations, individuals have different levels of status and different relations with others, and individuals with different levels of status usually show different behaviors in interpersonal communications [16–19]. Furthermore, in the marketing and service industries (e.g., banking, hospitality and tourism, and retail), customer loyalty programs are usually implemented based on membership tiers, and related consumer behaviors have attracted strong research interests [20, 21]. Consumers with different membership tiers have varying levels of importance for shopping sites and sellers who usually provide different levels of services for different membership tiers. As an example, compared with customers in low membership tiers, customers in high membership tiers tend to have higher behavioral loyalty [20, 21]. Reviewer information has also been found important in the literature. For example, Forman and Ghose [22] found that prevalence of reviewer disclosure of identity information was associated with increases in subsequent online product sales and suggested that identity-relevant information about reviewers shapes judgment of products and reviews of community members. Furthermore, consumers perceive customer-written product reviews as more helpful than those written by experts [23]. Membership has a negative moderating effect on the relationship between review objectivity and review credibility [24]. Liu and Park [25] found that the characteristics of review providers, such as disclosure of personal identity, expertise, and reputation, positively affect perceived usefulness of reviews. Extant literature focuses on the influence of user-generated contents for sellers and consumers as well as effects of disclosing reviewer information on performance outcomes. Additionally, some literature explored the antecedents of the characteristics of online reviews. For example, Goes et al. [26] found that popularity of users affects volume, objectivity and ratings of online product reviews posted by them; from the perspective of culture, Hong et al. [27] found that consumers from a collectivist culture are less likely to deviate from the average prior rating and to express emotion in their reviews; Huang et al. [28] investigated the effects of multiple psychological distances on online reviews. However, factors that lead the characteristics of online reviews have not received significant attention [26].

For sellers, customer relationship management is very important because higher-quality relationship results in greater customer commitment and more repeat purchases [29]. Furthermore, higher-quality relationship can significantly influence positive word-of-mouth [29, 30]. In turn, online review system or virtual community as a kind of online feedback mechanisms is helpful for customer relationship management [31]. Therefore, identifying different customers and their corresponding behaviors is crucially important for sellers to take corresponding management measures to improve sales performance, and that users' content generation behavior should receive equal attention as their consumption behavior in customer relationship management. In practice, online shopping sites (e.g., JD.com, TMall.com, and amazon.com) usually implement a customer membership tier management program in tandem with an online review system to incentive more content contributions and further disclose the status of membership tiers and username of reviewers on online communities. As an example, on the JD website, users' membership tiers are directly linked to their "website growth," which is determined by amount spent and number of reviews submitted. While membership tier programs are widely adopted, the effect of this kind of incentive mechanism on online reviews has not been investigated yet. Specifically, we seek to examine whether users with different membership tiers would show different content generation behaviors because of their ***status*** differences. Our research questions are:

(1) How does a customer's membership tier affect his or her review behavior?
(2) How does customer status directly and indirectly affect review helpfulness?

Based on previous research and theories related to status and online reviews, we first propose several hypotheses on the effects of status on user reviewing behavior, including rating, depth, and delay. Then, we further propose the direct and indirect effects of status on review helpfulness. To test our theoretical propositions, we collect online product review data from JD (www.jd.com, NASDAQ: JD), a leading online shopping site in China. Based on statistical and econometric analyses, we find that user content contribution behaviors change when tiers of the same reviewers are upgraded. Specifically, after controlling for reviewer, product and time fixed effects, compared with reviewers in low membership tiers, the (same) reviewers in high membership tiers tend to post online product reviews with higher review ratings, less review depth, and longer review delay. These findings shed light on research on the effect of status on user engagement in the context of online shopping and provide practical implications for B2C e-business, and contribute to research related to status. Understanding customers in different membership tiers exhibit different online review posting behaviors, online retailers could take corresponding managerial actions to improve customer experience and incentivize their engagement of providing product reviews.

The rest of this study is organized as follows. We first review related literature and develop research hypotheses. We then report empirical data, estimation method, and results of the analysis. Finally, we discuss results, limitations, and conclusions.

2 Literature review

Studies have investigated the effects of online product reviews on product sales and consumer decision making [9, 10, 32]. Researchers have focused on review rating, depth, and helpfulness [33, 34]. Moreover, extant studies have discussed factors that influence the intention of posting online reviews [35]. In the following subsections, we provide a concise review of the literature on online reviews to explain the context of our study and identify research gaps.

2.1 Online reviews

Review ratings and the content of online product reviews are associated with the reputation of online retailers and products, and they affect sales performance [10, 12]. Review helpfulness refers to the consumers' evaluation of the ability of online product reviews to provide diagnostic information of various products, which helps subsequent consumers make purchase decisions [13, 23]. Thus, review rating, content, and helpfulness have been important research topics recent years [13, 23, 36].

Online B2C shopping sites usually provide voting tools for consumers to evaluate helpfulness of online reviews. After reading an online review, review readers can click the "Yes" button to vote for review helpfulness. Review helpfulness reflects diagnosticity of product quality and has been measured as either "helpful for me to evaluate the product," "helpful in familiarizing me with the product," or "helpful for me to understand the product," therefore, review helpfulness is often adopted as a key measure of the ability to support purchase decision-making of online reviews [13, 37, 38].

Prior studies on review helpfulness provide important findings that laid the foundation for the present study. Key antecedents to online review helpfulness cover several areas. For example, review extremity (i.e., inclination to positive or negative) affects review helpfulness [13, 39–41]. Review depth has a positive effect on review helpfulness [13, 42]. Product type (search vs. experience product) may moderate the effects of review extremity and depth on review helpfulness [13, 43]. The source of online reviews (e.g., expert or ordinary customer; seller or consumer) and source credibility affect review helpfulness [23, 44, 45]. Finally, readability, consistency, semantic features, and stylistic characteristics have significant effects on review helpfulness [14, 23, 39, 41]. In addition, review timeliness may positively affect adoption of online reviews and recently posted online reviews are more likely to be considered by review readers [46].

To sum up, the literature on review helpfulness has ignored an important characteristic, i.e., the status of the reviewer. Most of the research has focused on effects of online reviews, and understanding is limited to the antecedents of online reviews that may affect online review posting behaviors (review rating, depth, and delay). In particular, reviewer status, although theoretically and practically important, has not been studied in the literature on online reviews. Thus, the present study seeks to address this gap.

2.2 Motivation, status, and status seeking

Researchers have investigated factors that affect product review behavior or word-of-mouth (WOM) from the perspective of reviewer motivation. Dichter [47] identified four factors that influence the posting of WOM: self-involvement or self-enhancement, as well as other, product, and message involvement. Balasubramanian and Mahajan [48] summarized motivations for positive WOM, i.e., focus-related utility, consumption utility, approval utility, and so on. Cheung and Lee [35] found that reputation, sense of belonging, and enjoyment in helping other consumers are significantly related to consumer intention to post eWOM. Motivations for positive or negative WOM may differ. As an example, consumers engage in positive WOM for altruistic, product involvement, and self-enhancement reasons; nevertheless, they engage in negative WOM for altruistic, anxiety reduction, retaliation, and advice-seeking reasons [49]. Other factors, such as attitude, perceived pressure, neuroticism, and conscientiousness, are significant predictors of individual intention to provide an online review [50].

Status was originally defined as one's standing in a social hierarchy as determined by respect, deference, and social influence [51]. Individuals strive not only for access to resources and material benefits, but also for intangibles, such as status, which is characterized by rank-ordered relationship among people associated with prestige and deference behavior [51]. Individuals pursue status because it provides access to greater economic and social resources, and they use such resources to improve their status [51]. An online review system is a reputation system that may confer the different network status of reviewers [31]. Status seeking as a social passion can drive participants to invest time and effort in sharing product reviews of their experience with others without direct benefit to themselves [52].

The status of the membership tier of a consumer is often conferred by a shopping site according to the level of his or her accumulated consumption and participation in the site (e.g., login times, quality and quantity of posting reviews). In turn, member loyalty programs favorably influence customer desires to increase their purchases [3]. While extant studies have focused on the effects and behavioral motivations of online reviews, limited research attention has been afforded to the effects of individual characteristics (such as status) on different aspects of reviews. In this study, we seek to address this void.

3 Hypotheses development

3.1 Theory and research framework

Individuals have different status in society or organizations and behave according to their respective status. Status refers to one's standing in a social hierarchy as determined by respect, deference, and social influence [51]. Status is "an effective claim to social esteem in terms of positive or negative privileges" [53]. In the context of work group, status theory [17, 54] proposes that workers care about their absolute wages and comparison of their wages with those earned by their co-workers. Further extension of status theory suggests that status competition based on merit can push group members to work harder [19]. A status characteristic is a characteristic of an actor who has two or more states that are differentially evaluated in terms of honor, esteem, or desirability, and each is associated with distinct moral and performance expectations. Therefore, status indicates beliefs on the performance and behavior of an individual possessing a given state of the characteristic [55]. Thye [56] analyzed the characteristics of status and developed status value theory, which asserts that exchangeable objects controlled by high-status actors are perceived to be more valuable when relevant to positive status. In turn, positive status characteristics accentuate perceived value of resources. Supporting this claim, Washington and Zajac [57] found that status was a significant predictor of whether a college was invited to participate in the National Collegiate Athletic Association postseason basketball tournament. As status is a valuable resource, people with higher status typically have higher power in negotiations and are provided more benefits in market interchanges [58], as well as credited with different personality traits by their co-subjects [59]. In a similar vein, Huberman et al. [60] found that observed subjects valued status independently of any monetary consequence and were willing to trade off some material gain to obtain higher status. Because status affects human interactions positively, people tend to seek status. Therefore, a successful advertising strategy is to associate high status with consumption of a product. In addition, high-status individuals may expect higher payoffs while low-status individuals may be more accepting of lower payoffs [58].

Berger et al. [55, 61] developed status characteristics and expectation state theory, which deals with processes whereby status differentials activate performance expectations and the effect of these expectations on human behavior, respectively. Driskell and Mullen [16] further proposed that status exerts its effects on behavior indirectly through the effects of status on expectations, and the effects of expectations on behavior. Status seeking consists of activities designed to improve an actor's standing in a group, and is therefore judged by the degree to which associated activities result in increasing prestige, honor, or deference. Once established, however, status could become a psychological asset for its holders who are reluctant to lose their status [62]. In addition, individuals with higher status are better at handling stress and are less prone to negative cognition [18].

In the context of online communities, prior studies found that status seeking is a social passion that drives participants to invest time and effort in sharing their experience with others without obtaining direct benefit themselves [52]. Correspondingly, position in the collaboration network influences the editor's decisions about her total contribution as well as the allocation of her efforts [63]. Considering online reviews are helpful for consumers to obtain more useful information and to make purchase decisions, posting online reviews can be considered as one of prosocial activities, thus it can bring social values for reviewers. Heyman and Ariely [64] found that individuals sometimes expend more effort in exchange for no payment (a social market) than they would expend when they receive a low payment (a monetary market). Furthermore, Ariely et al. [65] found that image motivation is more effective than monetary incentives for individuals to participate in public benefits and prosocial activities. Zhang and Zhu [66] also empirically proved that social benefits significantly affect content contributions at Chinese Wikipedia. In addition, Burtch et al. [67] compared the effectiveness of using financial incentives and social norms at stimulating online reviews, and found that financial incentives are more effective at inducing larger volumes of reviews, but the reviews that result are not particularly lengthy, whereas social norms have a greater effect on the length of reviews. Given online review is a typical public good and contributing online reviews is a prosocial behavior, it is reasonable to expect status to be relevant for online reviewing behaviors. In practice, online shopping websites usually associate membership tiers with engagements and content contributions of consumers and disclose user name and status of reviewers on online communities, which may bring reviewers social benefits such as reputational gains. Based on aforementioned literatures, we consider that theories related to status are applicable for this study.

Next, we employ status theory to explain the effects of status on review behavior, and its direct and indirect effects on review helpfulness. We first propose the effects of status (measured by membership tier) on review characteristics (review rating, depth, and delay) and review helpfulness. We further propose mediation effects of review rating, depth, and delay between status and review helpfulness to assess the direct and indirect effects of status on review helpfulness (see Fig. 1).

3.2 Membership tier and review behavior

3.2.1 Review rating

The review rating reflects the attitude or affection of reviewers to products. Some researchers consider review extremity as representing deviation extent from a neutral view and a general evaluation for product supportiveness [13, 68]. Previous research indicates that the product itself (e.g., quality, price, and popularity),

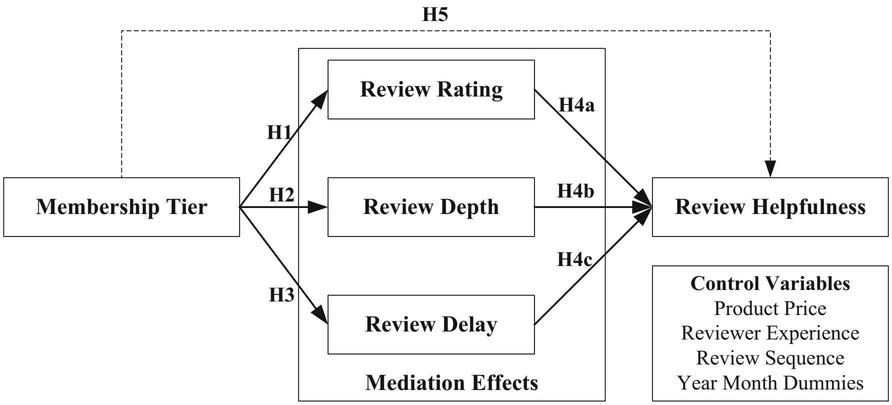

Fig. 1 Model of effects of membership tier on online reviews

consumer preference, and consumer traits influence review ratings, moreover, satisfaction and loyalty can positively affect positive WOM [69–71]. Based on the literature related to status and status seeking, individuals with higher status are better at handling stress and are less prone to negative cognition [52]. Furthermore, Kemper [18] proposed that status reduces wariness and defensiveness in others, and positive emotions of joy, caring, and loving continue to be associated with status providers. Therefore, considering that a shopping site is the provider of status, consumers with high-tier membership (vs. those with low-tier membership) might have more positive emotions and therefore intend to post more positive product reviews. Consequently, we propose the following hypothesis:

Hypothesis H1: Membership tier has a positive effect on review rating. Ceteris paribus, the higher the membership tiers, the higher the review rating.

3.2.2 Review depth and delay

Review depth reflects the richness of online reviews [42] and is measured by the number of words in the review [13, 72]. Review depth can reflect the engagement of reviewers because longer reviews require reviewers to invest more time, cognitive resource, and effort. Longer reviews often tend to include more product details, e.g., how and where the product is used. Additionally, longer reviews can provide better analysis of product quality and therefore are more helpful in facilitating the purchase decision process [13, 72].

After purchasing products, consumers need time to use products and post corresponding reviews after a certain time interval (termed as review delay, which also inversely reflects promptness of online reviews). Considering review timeliness can positively affect review helpfulness [46] which affects reviewer's status, if customers regard review generation important and value, they may have a strong motivation to post reviews promptly. Therefore, review delay is related to the experience duration of products and also is affected by the attention given by reviewers.

Customers in high-level membership tiers are more valuable to online retailers than customers in low-level membership tiers because they purchase more frequently and spend more money on websites. Thus, online retailers usually pay more attention and provide preferential services to customers in high membership tiers (e.g., price discounts, refunds, or changes). However, prior research related to status found that high-status individuals (vs. lower-status individuals) may become less motivated to make improvements [73]. Furthermore, high-status individuals may expect higher payoffs while lower-status individuals may be more accepting of lower payoffs [58]. As what mentioned before, review timeliness can positively affect review helpfulness [46] and longer reviews are more helpful in facilitating the purchase decision process. In practice, online shopping websites usually associate helpfulness of product reviews with the level of membership tiers for reviewers. Therefore, compared with consumers with high-tier memberships, consumers with low-tier membership have higher motivation to improve their status quickly by investing more efforts to post higher quality and possibly longer product reviews. Bearing the above in mind, we propose the following hypotheses.

Hypothesis H2: Membership tier has a negative effect on review depth. Ceteris paribus, the higher the membership tier, the less the review depth.

Hypothesis H3: Membership tier has a positive effect on review delay. Ceteris paribus, the higher the membership tier, the longer the review delay.

3.3 Review characteristics and helpfulness

Prior research has shown that review depth and rating affect review helpfulness [13, 72], and information timeliness affects information adoption [46]. In the same vein, we propose hypotheses H4a, H4b, and H4c.

3.3.1 Review rating and helpfulness

People place more weight on negative than on positive information in forming overall evaluations of a target [74], and this effect has been found in human perception as well as in product evaluation contexts [75]. Consumers tend to focus on negative information because it is more diagnostic, and therefore negative WOM is more influential than positive WOM [74]. Compared with positive WOM, negative WOM can attract more consumer attention and has more diagnosticity [44, 74]; thus, negative WOM may receive more chances to be browsed and voted for helpfulness. We therefore propose the following hypothesis.

Hypothesis H4a: Review rating has a negative effect on review helpfulness.

3.3.2 Review depth and helpfulness

Review depth reflects the amount of information in a review and measures cues of diagnosticity. Compared with product reviews with less depth, product reviews with more depth that contain richer experience information of product quality can be more easily adopted by consumers [13]. Extant prior studies have tested that review depth can positively affect review helpfulness. For instance, Wu et al. [15] found that longer product reviews could eliminate the effect of negativity bias on evaluation quality. Review depth can positively affect review helpfulness and product type can moderate the effect [13, 72]. Therefore, we propose the following hypothesis.

Hypothesis H4b: Review depth has a positive effect on review helpfulness.

3.3.3 Review delay and helpfulness

Review delay indicates timeliness of review information. Timely review information provides feedback to the current and the state of the art of a product/service [76, 77]. Review timeliness has been used in extant studies related to online reviews to measure the influence of product reviews. For example, Filieri and McLeay [46] found that review timeliness can positively affect review helpfulness. Generally, consumers first read product reviews that are posted earlier. Thus, consumers tend to make comments or vote for “helpfulness” earlier, which enable such reviews to easily accumulate more comments or votes for “helpfulness.” By contrast, a longer review delay results in less review timeliness and less review helpfulness. Accordingly, we propose the following hypothesis.

Hypothesis H4c: Review delay has a negative effect on review helpfulness.

3.4 Membership tier and review helpfulness

According to the theory of communication and persuasion [78, 79], information source is an influential factor on perceived credibility and communication performance for eWOM and traditional WOM. For instance, Connor et al. [80] found that product reviews of experts, compared with those of non-experts, are perceived as more helpful for purchase decisions. Furthermore, consumers care about e-opinion leadership or reviewer disclosure of identity information [81, 82]. In online shopping sites, customers with high-level membership tier (vs. those with low-level membership tier) tend to have more purchase experiences and may be considered as more credible sources of product reviews. As a result, membership tier might be positively associated with review helpfulness when the review characteristics are controlled for.

However, according to the hypotheses mentioned before, membership tier might have a positive effect on review rating and review delay which both affect review helpfulness negatively, which means membership tier should have a negative effect on review helpfulness through the mediation effects of review rating and review delay. What is more, membership tier might have a negative effect on review depth which might affect review helpfulness positively, which means membership tier also should have a negative effect on review helpfulness through the mediation effect of review depth. Accordingly, membership tier might negatively affect review helpfulness indirectly through the mediation effects of review rating, review depth and review delay.

According to aforementioned discussions, membership tier will have a positive effect on review helpfulness directly when review characteristics are controlled for and it will have a negative effect on review helpfulness indirectly through the mediation effects of review characteristics. Hence, we propose the following hypothesis.

Hypothesis H5: Membership tier has a direct positive effect on review helpfulness by controlling for review characteristics, and has an indirect negative effect on review helpfulness through the mediation effects of review characteristics.

4 Research methodology

The data of this study were collected from www.jd.com (Nasdaq: JD). JD is one of the leading online B2C retailers in China, with mosre than 60 million registered customers and nearly 10,000 vendors across the country.[1] Notably, JD provides an online user community for consumers to post product reviews (only purchasers can post corresponding comments). Furthermore, JD implements a membership-tier management strategy and classifies consumers into 10 tiers.[2] Membership tiers range from the lowest level of 1 to the highest level of 10 (e.g., the first level is referred to as register; the following levels are iron, bronze, silver, gold, one diamond, two diamonds, three diamonds, four diamonds, and the highest level is five diamonds). To facilitate the participation of more customers in the shopping site, JD associates the growth of membership tiers with the product reviews provided and the level of product consumption.[3] Therefore, data on online reviews from JD are suitable for empirical analysis in this study.

4.1 Data and samples

We used four criteria in selecting products and corresponding reviews in this study. First, considering the maximum number of membership tier levels, the number of online reviews for each product should not be less than 200. Second, to control the effect of product price on product reviews, the range of the product price should be as wide as possible. Third, to ensure a representative sample, the online reviews collected cover various types of products (search or experience products).[4] Therefore, we selected search products, including digital cameras, mobile phones, printers, and laptop computers, as well as experience products, including books,

[1] Information source: http://www.jd.com/intro/about.aspx.

[2] In October 15, 2013, the category of membership tiers was adjusted and classified into five grades. Sample data were extracted before the date and are not affected by the adjustment of membership tiers. Detailed information can be found at http://help.jd.com/help/question-57.html.

[3] The detailed rules for the growth of membership tiers can be found at http://help.jd.com/user/issue/163-368.html.

[4] With the development of the Internet and multiple new forms of media, traditional differences between search and experience goods have become blurred in the online environment [4, 87, 90]. To address this problem, a classification principle for search and experience products, depending on whether the dominant quality attributes are objective or subjective, has been proposed and applied [4, 13, 87, 90].

CDs/DVDs, food, and cosmetics [13, 83–85] in our study. Finally, to control for the effect of service quality on product reviews, the products collected are all independently provided and operated only by JD itself to ensure identical logistics and service.

Following the aforementioned criteria, we collected product reviews of 157 products posted between November 2008 and April 2013 from the JD website. According to JD's membership tier policy, the website updates its customer membership tier based on consumption and engagement on the website. Therefore, the sample data set spans four years and may include customers whose membership tiers have been upgraded during that period. Considering that the overall sample contains numerous reviewers and spans four years, many reviewers may have experienced a dynamic upgrade of membership tier.[5] Therefore, we extracted the reviews posted by reviewers who experienced a dynamic upgrade of membership tier from the overall sample, and then we ran panel-data fixed effect regressions to check the effect of reviewer membership tier upgrades on their own reviews.

Balancing sample size with the upgrade range of membership tiers for each reviewer, we set two criteria for extracting the subsample from the overall sample. First, to ensure within-reviewer variation of status, each reviewer should experience an upgrade of at least three membership tiers. The reason is that for the panel data from the overall sample, too narrow a variation range of membership tiers for each reviewer may lead to asymmetrical distribution of membership tiers between reviewers. By contrast, too wide a variation range may result in a small sample size. Second, for each reviewer, only the earliest review for each product should be extracted. Because reviewers in high membership tiers may repeatedly purchase a certain product, a possibility exists that many reviewers post reviews for a certain product repeatedly. Later reviews may be posted quickly because corresponding products do not need to be experienced again. Thus, later product reviews should be eliminated to run regressions. Following the aforementioned two criteria, we extracted 1014 reviewers from the overall samples and obtained 32,543 reviews posted by these reviewers, covering 157 products (83 search and 74 experience products, as shown in Table 1).

Finally, for each product and each online review, we collected the following information from the JD website: product name, product price, reviewer identification, reviewer membership tier at posting time, review rating, review content, purchase time, review time, and number of helpfulness votes by readers.

4.2 Variables and measurement

As an explanatory variable, membership tier (Tier) is an interval variable. The shopping site used in this study classified membership tiers into 10 levels. Therefore, the values of Tiers are set as digits ranging from 1 to 10. Each dependent variable is quantified as follows: review ratings (Rating, i.e., star rating vote results

[5] At the time of the data collection, we were able to observe the same reviewers with multi-level membership tiers in this data set. That is to say, JD website used to record the level of membership tier of the reviewer at that time for each online review. However, the current version of the website only shows the current status of reviewers.

Table 1 Products used in this study

Product	Number of products	Number of reviews	Source	Product	Number of products	Number of reviews	Source
Digital camera	30	3760	[84, 86]	Food	28	3053	[85]
Mobile phone	30	5686	[87]	Cosmic	46	16,332	[85]
Laptop computer	10	408	[88]				
Printer	13	3304	[83]				
Total	83	13,158		Total	74	19,385	

for a product) are set as digit ranging from one to five; review depth (Depth) is measured by the number of words contained in the review (i.e., word count) [13, 42]; review delay (Delay) is measured by the time interval between posting review and produce purchase; and review helpfulness (noted as Helpful) is measured as the number of helpfulness votes received by a review [13].

We add several control variables in this study. For example, product prices may affect customer satisfaction [89], and therefore may affect online reviews. Thus, we consider product price as a control variable and label it "Price". Customers have less incentive to spend time to post reviews if previous reviews provide sufficient information [90]. Therefore, the time sequence of reviews for each product is another control variable (labeled as Seq). Table 2 provides detailed information for all variables in this study. In addition, considering that consumer shopping experiences may affect their subsequent shopping and review posting, we added a variable to number each consumer experience according to the sequence of purchase date (labeled as Exp).

4.3 Descriptive statistics and correlation

Table 3 shows descriptive statistics of variables for the samples. Table 4 presents descriptive statistics for variables at each membership tier level. The results indicate that means of review ratings are all greater than 4. The ratings for all products tend to be positive, and the review depth, delay, as well as product price, sequence, and experience all have significant deviations. Nevertheless, membership tiers are not well-distributed and the tier level of 9 has no data, which should be treated specially.

The correlation coefficient results among the variables (see Table 5) indicate that membership tier is significantly associated with all the dependent variables. Membership tier is significantly positively related to review rating, delay, and helpfulness, but is significantly negatively related to review depth. Furthermore, review helpfulness is significantly positively related to review depth, but negatively related to review rating and delay.

Table 2 Measurements for variables

Variables	Measurements for variables	Metric	Source
Tier	Convert the classification of membership tiers to corresponding integers	Nonnegative integer, 1–10	As per classification of membership tiers from the online retailer
Rating	Star ratings of reviews to indicate review rating	Nonnegative integer, 1–5	[13, 91]
Depth	Word count of reviews to indicate review depth	Nonnegative integer	[13, 42]
Delay	Number of days between posting reviews and purchasing products	Nonnegative integer	Defined in this study
Helpful	Number of helpfulness votes for online reviews	Nonnegative integer	[13]
Price	Product price, RMB currency unit	Nonnegative, float	[89]
Seq	Sequence of reviews for each product, 1 represents the first review for a product	Integer, greater than 0	[90]
Exp	Reviewer's purchase experience measured by the sequence of purchase date, 1 represents the earliest purchase for each reviewer	Integer, greater than 0	

Table 3 Descriptive statistics for full samples (obs. N = 32,543)

Variables	Mean	SD	Min	Max
Tier	3.036	1.166	1	10
Rating	4.680	0.671	1	5
Depth	46.702	50.653	3	833
Delay	31.247	39.870	1	182
Helpful	0.047	0.560	0	34
Price	841.061	1646.550	14.9	19,999
Seq	17,260.530	21,258.250	1	101,347
Exp	22.401	17.401	1	97

Seq was coded from the overall sample, and thus, its maximum value was out of the range in this sample

4.4 Empirical analysis

The proposed model (see Fig. 1) features three mediators (review rating, depth, and delay) simultaneously. We first presented parameter estimations (Fig. 2) with an integrated approach using "PROCESS" methods suggested by Preacher and Hayes [92] and Hayes [93]. These methods deal with multiple mediator relationships. Bootstrap methods were used for inference on indirect effects of membership tier on review helpfulness through review rating, depth, and delay. A similar approach has been used in extant IS [94] and marketing studies [95]. Second, we performed the analysis using panel data econometric methods to correct for potential unobserved

Table 4 Descriptive statistics for membership tiers

Variables	Obs	Mean	SD	Min	Max	Obs	Mean	SD	Min	Max
	Tier = 1					Tier = 6				
Rating	698	4.539	0.855	1	5	641	4.805	0.519	1	5
Depth	698	48.665	45.682	7	575	641	39.963	47.140	7	833
Delay	698	15.944	22.706	1	178	641	30.284	38.226	1	178
Helpful	698	0.063	0.615	0	12	641	0.034	0.677	0	17
	Tier = 2					Tier = 7				
Rating	12,947	4.624	0.717	1	5	74	4.892	0.313	4	5
Depth	12,947	47.475	50.310	3	586	74	39.500	38.918	15	258
Delay	12,947	28.636	37.355	1	181	74	29.081	33.356	2	147
Helpful	12,947	0.037	0.541	0	34	74	0.027	0.163	0	1
	Tier = 3					Tier = 8				
Rating	8953	4.700	0.658	1	5	8	4.875	0.354	4	5
Depth	8953	46.285	51.640	5	575	8	48.375	34.063	15	93
Delay	8953	32.741	38.963	1	182	8	25.750	23.469	3	66
Helpful	8953	0.049	0.474	0	21	8	0	0	0	0
	Tier = 4					Tier = 9				
Rating	5193	4.704	0.635	1	5					
Depth	5193	49.855	54.080	3	591					
Delay	5193	32.764	42.466	1	181					
Helpful	5193	0.057	0.607	0	19					
	Tier = 5					Tier = 10				
Rating	4027	4.789	0.547	1	5	2	5	0.000	5	5
Depth	4027	41.949	45.904	5	689	2	19.5	2.121	18	21
Delay	4027	37.194	46.992	1	180	2	88.5	88.388	26	151
Helpful	4027	0.058	0.689	0	30	2	0	0	0	0

Table 5 Pearson correlation coefficients between variables

Variables	Tier	Rating	Depth	Delay	Helpful
Tier	1				
Rating	0.088***	1			
Depth	−0.026***	−0.220***	1		
Delay	0.072***	0.063***	−0.101***	1	
Helpful	0.010*	−0.237***	0.212***	−0.026***	1

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

heterogeneity as robustness analyses by controlling for multiple fixed effects (reviewer, product, and time levels). Based on conventional approaches, we took a natural logarithm for variable review delay and helpfulness of which the value was added by one for a logarithm process conveniently because of helpfulness could be zero.

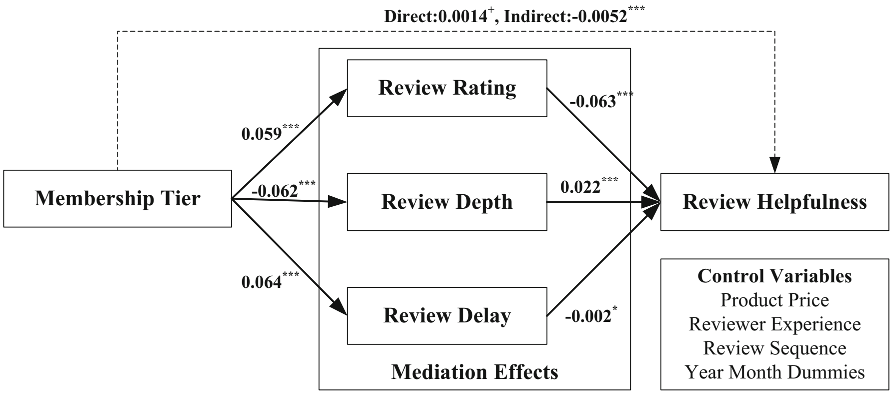

Fig. 2 Estimation results of mediation model. *Note* ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, $+p<0.1$

4.4.1 Hypotheses testing

Figure 2 shows the main results. All path coefficients were the estimated values for each relationship. First, Tier had significant positive effects on Rating ($\beta = 0.059$, $p < 0.001$) and Delay ($\beta = 0.064$, $p < 0.001$), and had a significant negative effect on Depth ($\beta = -0.062$, $p < 0.001$). In other words, when membership tiers of reviewers upgrade each level, corresponding review rating, delay and length may increase 5.9, 6.4% and decrease 6.2% on average respectively (without consideration of logarithm process for review delay and review depth). Thus, H1, H2, and H3 were all supported. Second, we empirically tested the effects of Tier, Rating, Depth, and Delay on Helpfulness. Tier had a significant effect on Helpfulness ($\beta = 0.0014$, $p < 0.1$), although the effect size of Tier was significantly smaller than that of Rating ($\beta = -0.063$, $p < 0.001$), Depth ($\beta = 0.022$, $p < 0.001$) and Delay ($\beta = -0.002$, $p < 0.05$). Obviously, the effects of review rating, review depth and review delay on review helpfulness were much greater than that of membership tier. Thus, H4a, H4b, and H4c were all supported. Tier had a positive direct albeit marginally significant effect on Helpfulness ($\beta = 0.0014$, $p < 0.1$) and had significant effects on Rating, Depth, and Delay, which implied that its effects on Helpfulness was mediated by Rating, Depth, and Delay. Therefore, H4 was supported.

To sum up, the effect of Tier on Helpfulness was mediated by Rating, Depth, and Delay. Tier directly increased Helpfulness, but the effect was significantly mediated by Rating, Depth, and Delay, finally the general mediation effects were negative. To validate these results, we used a bootstrap method proposed by Preacher and Hayes [92] to estimate these bias-corrected indirect effects of Tier on Helpfulness through Rating, Depth, and Delay. We presented bootstrap standard errors and confidence intervals in Table 6.

As shown in Table 6, the direct effect of membership tier on review helpfulness was only marginally different from zero ($p < 0.10$), but the indirect effect of

Table 6 Direct and bias corrected indirect effects of membership tier on helpfulness

		Estimate	SE	p	Confidence Interval
Direct		0.0014	0.0008	0.069	(−0.001, 0.0028)
Indirect	Total	−0.0052	0.0004	0.000	(−0.006, −0.0044)
	Rating	−0.0037	0.0003	0.000	(−0.0043, −0.0030)
	ln (Depth)	−0.0014	0.0002	0.000	(−0.0017, −0.0011)
	ln (Delay)	−0.0001	0.0000	0.017	(−0.0002, −0.000)

Number of bootstrap samples for bias-corrected bootstrap confidence intervals: 5000 times; level of confidence for all confidence intervals in output: 95%

membership tier on review helpfulness via Rating, Depth, and Delay was significant. Apparently, the total indirect effect (−0.0052) was larger than the direct effect (0.0014) of membership tier on review helpfulness. That is the effect of membership tier on review helpfulness was mostly mediated by Rating, Depth, and Delay. To assess indirect effects, Preacher and Hayes [92] recommended base inference on indirect effect and not entirely on statistical significance of the path coefficient estimates. Thus, inference should be based on an explicit quantification of the indirect effect itself and a statistical test that respects the non-normality of the sampling distribution of the indirect effect. Out of several available approaches, asymmetric bootstrap confidence interval estimates is the most widely recommended procedure [93]. As Table 6 shows, the bias-corrected indirect effects of Rating, Depth, and Delay were negative (total indirect effect was −0.0052) and statistically different from zero, as evidenced by a 95% bias-corrected bootstrap confidence intervals that were entirely above zero. For Rating, 95% confidence interval range was −0.0043 to −0.0030; for ln(Depth), 95% confidence interval range was −0.0017 to −0.0011; and for ln(Delay), 95% confidence interval range was −0.0002 to −0.000. The results of the mediation analysis suggested that high-status reviewers in general write less helpful reviews (indirect effects), but those reviews are considered more helpful when review characteristics are controlled for (direct effect).

4.4.2 Econometric analysis using panel data

To correct for potential unobserved heterogeneity (e.g., reviewer level, product level, and time level), which may affect the robustness of the preceding analyses, we further conduct a series of econometric analyses to check the robustness of the main results.

Because the membership tier upgrading for different reviewers do not usually occur simultaneously, no uniform cross-section exists at a certain point-in-time for the entire group of reviewers. Thus, to test the effect of dynamic upgrades in membership tiers on product reviews for reviewers themselves, we considered each reviewer ID as a panel ID variable. Then, we used each level of membership tier for each product as a cross-section observation of the panel data and ran panel data regressions of dependent variables on membership tiers. Although the exact upgrade time of each membership tier was unavailable, the month of posting time of each online review (noted as Year_Month) could be approximately taken as the time series of the panel data and be used as a dummy variable in this panel data regression. In addition, we also controlled for product-level fixed effect with dummy variables. Given that review ratings might be associated with review depth and delay, we also controlled for rating in estimating the review depth and delay. In the following equations, *i* represents reviewers, *j* represents products, and *t* represents time (Year_Month). In sum, we used a reviewer–product–time three-way fixed effect model for econometric identification.

$$\begin{aligned}\mathrm{Rating_{ijt}} &= \beta_1 * \mathrm{Tier_{it}} + \beta_2 * \ln(\mathrm{Price_{jt}}) + \beta_3 * \ln(\mathrm{Seq_{ijt}}) \\ &\quad + \beta_4 * \ln(\mathrm{Exp_{it}}) + \mu_i + \alpha_j + \theta_t + \varepsilon_{ijt}\end{aligned} \tag{1}$$

$$\begin{aligned}\ln(\mathrm{Depth})_{ijt} &= \beta_1 * \mathrm{Tier_{it}} + \beta_2 * \mathrm{Rating_{ijt}} + \beta_3 * \ln(\mathrm{Price_{jt}}) + \beta_4 * \ln(\mathrm{Seq_{ijt}}) \\ &\quad + \beta_5 * \ln(\mathrm{Exp_{it}}) + \mu_i + \alpha_j + \theta_t + \varepsilon_{ijt}\end{aligned} \tag{2}$$

$$\begin{aligned}\ln(\mathrm{Delay})_{ijt} &= \beta_1 * \mathrm{Tier_{it}} + \beta_2 * \mathrm{Rating_{ijt}} + \beta_3 * \ln(\mathrm{Price_{jt}}) \\ &\quad + \beta_4 * \ln(\mathrm{Seq_{ijt}}) + \beta_5 * \ln(\mathrm{Exp_{it}}) + \mu_i + \alpha_j + \theta_t + \varepsilon_{ijt}\end{aligned} \tag{3}$$

$$\begin{aligned}\ln(\mathrm{Helpful})_{ijt} &= \beta_1 * \mathrm{Tier_{it}} + \beta_2 * \ln(\mathrm{Price_{jt}}) + \beta_3 * \ln(\mathrm{Seq_{ijt}}) + \beta_4 * \ln(\mathrm{Exp_{it}}) \\ &\quad + \mu_i + \alpha_j + \theta_t + \varepsilon_{ijt}\end{aligned} \tag{4}$$

$$\begin{aligned}\ln(\mathrm{Helpful})_{ijt} &= \beta_1 * \mathrm{Tier_{it}} + \beta_2 * \mathrm{Rating_{ijt}} + \beta_3 * \ln(\mathrm{Depth})_{ijt} + \beta_4 * \ln(\mathrm{Delay})_{ijt} \\ &\quad + \beta_5 * \ln(\mathrm{Price_{jt}}) + \beta_6 * \ln(\mathrm{Seq}_{ijt}) + \beta_7 * \ln(\mathrm{Exp_{it}}) + \mu_i + \alpha_j + \theta_t + \varepsilon_{ijt}\end{aligned} \tag{5}$$

All equations include reviewer-specific fixed effects (estimated with within transformation) to capture idiosyncratic and time-invariant unobserved characteristics associated with each reviewer. Equation (1) includes product-specific and time-specific fixed effects (estimated with dummy variables) that captured any influence on dependent variables because of timing differences in each category. The advantage of fixed effect estimation is that it controls for intrinsic characteristics of product and reviewer, which inherently affects dependent variables. In addition, fixed effect estimation allows the error term ε_{ijt} to be arbitrarily correlated with other unobserved explanatory variables, thereby making the estimation results more robust. Furthermore, we chose panel data analysis with fixed effects because Hausman tests (for the reviewer fixed effect) between random and fixed effects strongly favored the latter as a more robust approach.

Given that observations of membership tier levels from 7 to 10 were very limited, we used the aforementioned panel data to run two stages of regressions for tier level lower than 7. Thus, observational number of reviews was reduced to 32,459 from 32,543. Nevertheless, the results were consistent if we used the entire data set. We first ran an OLS regression for each dependent variable to establish baseline findings. Second, we ran a panel data linear regression with fixed effects for each dependent variable. The regression results were reported in Tables 7 and 8. As shown in Table 7, the explanatory level of our regression models for Rating, Depth and Delay got about 6, 13 and 18% or so respectively.

4.4.3 Summary of hypotheses testing

For hypotheses H1, H2, and H3, we expected that the coefficient of Tier on Rating would be positive and significant, the coefficient of Tier on ln(Depth) would be negative and significant, and the coefficient of Tier on ln(Delay) would be positive and significant. As shown in Table 7, the results from the two stages of the regressions are consistent with our expectations. Therefore, H1, H2, and H3 are all strongly supported.

For hypotheses H4a, H4b, and H4c, we expected that the coefficient of Rating on ln(Helpful) would be negative and significant, the coefficient of ln(Depth) on ln(Helpful) would be positive and significant, and the coefficient of ln(Delay) on ln(Helpful) would be negative and significant. As for H5, owing to mediation effect of review rating, depth, and delay, compared with Eq. (4), the significance level

Table 7 Regression results of OLS and FE

Variables	(1) OLS Rating	(2) FE Rating	(3) OLS ln(Depth)	(4) FE ln(Depth)	(5) OLS ln(Delay)	(6) FE ln(Delay)
Tier	0.047***	0.046***	−0.044***	−0.043***	0.062***	0.056***
	(0.003)	(0.004)	(0.003)	(0.003)	(0.006)	(0.007)
ln(Price)	−0.011	−0.141	−0.077	0.120	−0.094	−0.111*
	(0.011)	(0.104)	(0.078)	(0.076)	(0.091)	(0.067)
ln(Seq)	0.005	0.005	−0.006	−0.006	0.139***	0.137***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.007)	(0.007)
ln(Exp)	−0.030***	−0.016	0.023***	0.019	−0.029**	0.004
	(0.007)	(0.017)	(0.007)	(0.017)	(0.012)	(0.029)
Rating			−0.184***	−0.183***	0.053***	0.043***
			(0.007)	(0.007)	(0.009)	(0.009)
Constant	4.833	5.344***	5.936	5.244***	2.495	2.678***
	(0.364)	(0.386)	(0.488)	(0.849)	(2.402)	(0.598)
Reviewer FE	No	Yes	No	Yes	No	Yes
Year_Month effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	32,459	32,459	32,459	32,459	32,459	32,459
R-squared (within)	0.062	0.057	0.132	0.126	0.186	0.171
Number of reviewers	1014	1014	1014	1014	1014	1014

Cluster robust standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. For the preceding panel data linear regressions, the p values of the Hausman test between corresponding random and fixed effects are all less than 0.001

Table 8 Regression results for review helpfulness

Variables	(1) OLS ln(Helpful)	(2) FE ln(Helpful)	(3) OLS ln(Helpful)	(4) FE ln(Helpful)
Tier	−0.003***	−0.002***	0.002**	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)
Rating			−0.063***	−0.063***
			(0.004)	(0.004)
ln(Depth)			0.021***	0.022***
			(0.002)	(0.002)
ln(Delay)			−0.003***	−0.003***
			(0.001)	(0.001)
ln(Price)	−0.072	0.033	−0.071	0.021
	(0.071)	(0.029)	(0.391)	(0.025)
ln(Seq)	−0.002*	−0.002**	−0.001	−0.002
	(0.001)	(0.001)	(0.001)	(0.001)
ln(Exp)	0.001	−0.002	−0.002	−0.004
	(0.002)	(0.004)	(0.002)	(0.004)
Constant	1.226	0.875	1.430	1.131
	(1.226)	(0.792)	(1.613)	(0.767)
Observations	32,459	32,459	32,459	32,459
R-squared (within)	0.046	0.046	0.130	0.131
Number of reviewers	1014	1014	1014	1014

Cluster robust standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. For the above panel data linear regressions, the p values of the Hausman test between the corresponding random and fixed effects are all less than 0.01

Table 9 Summary of findings

Hypothesis	Description	Result
H1	Membership tier has a positive effect on review rating	Supported
H2	Membership tier has a negative effect on review depth	Supported
H3	Membership tier has a positive effect on review delay	Supported
H4a	Review rating has a negative effect on review helpfulness	Supported
H4b	Review depth has a positive effect on review helpfulness	Supported
H4c	Review delay has a negative effect on review helpfulness	Supported
H5	Membership tier has a direct positive effect on review helpfulness, whereas has an indirect negative effect on review helpfulness through the mediation effects of review characteristics	Supported

becomes lower and the coefficient of Tier on ln(Helpful) may change direction. As shown in Table 8, the results from the two stages of regressions are consistent with our expectations. Therefore, H5, H4a, H4b, and H4c are all strongly supported. Table 9 shows the summary of findings.

5 Discussion and conclusions

5.1 Key findings

The results of this study indicate that membership tier has a positive effect on review rating and a negative effect on review depth and delay. Thus, all hypotheses proposed in the study are statistically supported.

Review rating is a reflection of customer attitudes and affective tendencies toward sellers [13, 68], whereas membership tier is positively associated with review rating. Thus, compared with reviews posted by customers in low membership tiers, reviews posted by customers in high membership tiers tend to reflect more positive attitudes and affective tendencies to online retailers. Review depth reflects information diagnosticity and online review quality to a certain extent [8, 13, 37]. Moreover, review depth has a positive effect on review helpfulness [13, 42]. Because membership tier is negatively associated with review depth, a higher level of membership may result in lower review quality compared with lower level membership tiers. Interestingly, although users with a higher membership tier produce lower-quality content, their reviews are perceived as more helpful when review characteristics are controlled for, possibly because of their higher status.

5.2 Theoretical contributions

The present study sheds light on behavioral research on online product reviews from the perspective of user status and provides several theoretical contributions.

First, we examined the effects of reviewer status on the characteristics of online product reviews. The findings are the first to explain the antecedents of reviewer status (namely, membership tiers) in online product reviews. These results suggest that the motivation of status seeking may stimulate community members to participate in user content generation, but may result in variations on the characteristics of product reviews among customers in different membership tiers. Previous studies have reported adequate findings on the effects of product review itself (or WOM) on consumer decision making and product sales [9, 10, 32]. Researchers have explored the relationship between information source (e.g., disclosure of personal identity and reviewer expertise or customers) and review helpfulness or credibility [22–25]. Nevertheless, consumer status of membership tiers as an antecedent of the characteristics of product reviews has not been explored. This finding addresses the research gap concerning the effects of membership tiers on product reviews. Future research may continue to explore the antecedents of the characteristics of product reviews.

Second, we examined the mediation effect on the relation between reviewer status and review helpfulness. Prior research on information source in online reviews primarily focused on direct effects on review helpfulness or credibility but ignored the mediation effect of the characteristics of online review itself [22–25]. We found that the information source of reviewer status may affect online review helpfulness directly, but the direction of this effect would be reversed by the mediation effect of the characteristics of the online review itself. Thus, this finding suggests that the antecedents of product reviews should consider this mediation effect.

In addition, we use theories related to status to explain the effects of membership tier on the characteristics of online reviews and review helpfulness from the perspective of status. This factor is seldom used in the IS literature. Considering the widespread use of membership tier management strategy in online and offline shopping, we hope that this study may open new avenues for future IS research from the perspective of consumer status.

5.3 Practical implications

For online shopping websites, identifying and managing membership tiers is easy because these factors are assigned by online shopping sites based on the level of consumer consumption and participation in the embedded user community. Because of the predictive value of customer membership tiers on consumption and online reviews, online shopping sites may consider measures to improve sales and online review systems. The membership tier management strategy may encourage reviewers with high membership tiers to post more positive online reviews, and thus improve retailer reputation and sales. At the same time, review depth and perceived review helpfulness may decrease with membership tiers. Therefore, our suggestions for the online shopping sites are as follows:

1) Refine strategies to encourage customers to post deeper and more valuable product reviews that can aid in consumer shopping decisions more effectively. For instance, growth of membership tiers should be associated with quantity and quality of user-generated contents (e.g., review depth, delay, and helpfulness). Other than membership tier mechanism, reviewers should be endowed with a different network status (e.g., a badge) according to their contributions. This strategy is expected to stimulate consumers to contribute more reviews to enhance their status.
2) Improve the online review system. For instance, disclosing the status of reviewers (e.g., membership tiers and statistics of contributions on the user community) will motivate consumers to seek status by posting more reviews with high quality. By providing multiple types of sorting functions (e.g., sorting by consumer status, rating, length, posting time, helpfulness, and responded comments), consumers will appreciate the ease in finding helpful reviews.

5.4 Limitations and suggestions for future research

This study has several limitations. First, we did not directly measure the concept of perceived status by measuring reviewer psychological activities via a survey or questionnaire for reviewers, but only took membership tier as reviewers' status. Future research could administer a survey or conduct controlled laboratory experiments to pinpoint the exact mechanism that leads to observed effects. Future studies may enrich or refine evaluation variables for online reviews by other methods (e.g., text mining, affective analysis, and stylistic analysis).

Second, dependent variables in this study were limited to review rating, depth, delay, and helpfulness. We did not conduct further review content analysis, such as for readability, style, and consistency. Thus, future studies could explore linguistic characteristics of the content of the reviews to understand the effects of status (membership tiers) on reviews.

This study provides improved understanding of effects of the status and engagement of customers on user-generated content, and offers new directions for future research on the behavior of online reviews. Future research may further exploit other aspects of online reviews (e.g., relevance and readability) or other attributes of consumers (e.g., gender, education, and prior knowledge) to evaluate the heterogeneous effects of status and engagement on customer online reviews. In addition, interested researchers may extend this research to other contexts, such as independent third-party consumer communities, or to other cultural environments.

5.5 Conclusions

Online shopping sites that implement membership-tier management strategy associated with the level of customer engagement in the product community can motivate consumers to contribute user-generated content for status seeking. However, with the growth of membership tiers, consumers tend to exert less effort and more positive attitude toward product reviews. This observation is expected to lead to low quality or helpfulness of reviews as perceived by review readers. This finding enriches the literature related with antecedents of product reviews and provides a new perspective of status for IS research in user-generated content and e-commerce platforms. Additionally, we provide practical suggestions to improve the online reviews of shopping sites.

Acknowledgements Funding was provided by National Natural Science Foundation of China (Grant No. 71331007), Capital University of Economics and Business (Grant No. 00791554410262) and National Planning Office of Philosophy and Social Science (Grant No. 15AGL001).

References

1. Lacey, R., & Sneath, J. Z. (2006). Customer loyalty programs: Are they fair to consumers? *Journal of Consumer Marketing, 23*(7), 458–464.
2. Meyer-Waarden, L. (2008). The influence of loyalty programme membership on customer purchase behaviour. *European Journal of Marketing, 42*(1/2), 87–114.
3. Lacey, R. (2009). Limited influence of loyalty program membership on relational outcomes. *Journal of Consumer Marketing, 26*(6), 392–402.
4. Klein, L. R. (1998). Evaluating the potential of interactive media through a new lens: Search versus experience goods. *Journal of Business Research, 41*(3), 195–203.
5. Kwark, Y., Chen, J., & Raghunathan, S. (2014). Online product reviews: Implications for retailers and competing manufacturers. *Information Systems Research, 25*(1), 93–110.
6. Olshavsky, R. W., & Granbois, D. H. (1979). Consumer decision making-fact or fiction? *Journal of Consumer Research, 6*(2), 93–100.

7. Park, D. H., & Lee, J. (2009). eWOM overload and its effect on consumer behavioral intention depending on consumer involvement. *Electronic Commerce Research and Applications, 7*(4), 386–398.
8. Pavlou, P. A., & Dimoka, A. (2006). The nature and role of feedback text comments in online marketplaces: Implications for trust building, price premiums, and seller differentiation. *Information Systems Research, 17*(4), 392–414.
9. Zhang, J. Q., Craciun, G., & Shin, D. (2010). When does electronic word-of-mouth matter? A study of consumer product reviews. *Journal of Business Research, 63*(12), 1336–1341.
10. Berger, J., Sorensen, A. T., & Rasmussen, S. J. (2010). Positive effects of negative publicity: When negative reviews increase sales. *Marketing Science, 29*(5), 815–827.
11. Clemons, E. K., Gao, G. G., & Hitt, L. M. (2006). When online reviews meet hyperdifferentiation: A study of the craft beer industry. *Journal of Management Information Systems, 23*(2), 149–171.
12. Dellarocas, C. (2006). Strategic manipulation of internet opinion forums: Implications for consumers and firms. *Management Science, 52*(10), 1577–1593.
13. Mudambi, S. M., & Schuff, D. (2010). What makes a helpful online review? A study of customer reviews on Amazon. com. *MIS Quarterly, 34*(1), 185–200.
14. Schindler, R. M., & Bickart, B. (2012). Perceived helpfulness of online consumer reviews: The role of message content and style. *Journal of Consumer Behaviour, 11*(3), 234–243.
15. Wu, P. F., Van der Heijden, H. & Korfiatis, N. (2011). The influences of negativity and review quality on the helpfulness of online reviews, Shanghai: ICIS 2011 Proceedings.
16. Driskell, J. E., & Mullen, B. (1990). Status, expectations, and behavior a meta-analytic review and test of the theory. *Personality and Social Psychology Bulletin, 16*(3), 541–553.
17. Frank, R. H. (1985). *Choosing the right pond: Human behavior and the quest for status*. Oxford: Oxford University Press.
18. Kemper, T. D. (1991). Predicting emotions from social relations. *Social Psychology Quarterly, 54*(4), 330–342.
19. Loch, C. H., Huberman, B. A., & Stout, S. (2000). Status competition and performance in work groups. *Journal of Economic Behavior & Organization, 43*(1), 35–55.
20. Tanford, S. (2013). The impact of tier level on attitudinal and behavioral loyalty of hotel reward program members. *International Journal of Hospitality Management, 34*(September), 285–294.
21. Tanford, S., Raab, C., & Kim, Y. (2011). The influence of reward program membership and commitment on hotel loyalty. *Journal of Hospitality & Tourism Research, 35*(3), 279–307.
22. Forman, C., Ghose, A., & Wiesenfeld, B. (2008). Examining the relationship between reviews and sales: The role of reviewer identity disclosure in electronic markets. *Information Systems Research, 19*(3), 291–313.
23. Li, M., Huang, L., Tan, C., & Wei, K. (2013). Helpfulness of online product reviews as seen by consumers: Source and content features. *International Journal of Electronic Commerce, 17*(4), 101–136.
24. Luo, C., Luo, X. R., Xu, Y., Warkentin, M., & Sia, C. L. (2014). Examining the moderating role of sense of membership in online review evaluation. *Information & Management, 52*(3), 305–316.
25. Liu, Z., & Park, S. (2015). What makes a useful online review? Implication for travel product websites. *Tourism Management, 47*(4), 140–151.
26. Goes, P. B., Lin, M., & Au Yeung, C. (2014). "Popularity effect" in user-generated content: Evidence from online product reviews. *Information Systems Research, 25*(2), 222–238.
27. Hong, Y., Huang, N., Burtch, G., & Li, C. (2016). Culture, conformity, and emotional suppression in online reviews. *Journal of the Association of Information Systems*, *17*(11), 737–758.
28. Huang, N., Burtch, G., Hong, Y., & Polman, E. (2016). Effects of multiple psychological distances on construal and consumer evaluation: A field study of online reviews. *Journal of Consumer Psychology, 26*(4), 474–482.
29. Kim, W. G., Han, J. S., & Lee, E. (2001). Effects of relationship marketing on repeat purchase and word of mouth. *Journal of Hospitality & Tourism Research, 25*(3), 272–288.
30. Gremler, D. D., Gwinner, K. P., & Brown, S. W. (2001). Generating positive word-of-mouth communication through customer-employee relationships. *International Journal of Service Industry Management, 12*(1), 44–59.
31. Dellarocas, C. (2003). The digitization of word of mouth: Promise and challenges of online feedback mechanisms. *Management Science, 54*(3), 460–476.
32. Duan, W., Gu, B., & Whinston, A. B. (2008). The dynamics of online word-of-mouth and product sales—An empirical investigation of the movie industry. *Journal of Retailing, 84*(2), 233–242.

33. Gopinath, S., Thomas, J. S., & Krishnamurthi, L. (2014). Investigating the relationship between the content of online word of mouth, advertising, and brand performance. *Marketing Science, 33*(2), 1–19.
34. Hu, N., Koh, N. S., & Reddy, S. K. (2014). Ratings lead you to the product, reviews help you clinch it? The mediating role of online review sentiments on product sales. *Decision Support Systems, 57*(1), 42–53.
35. Cheung, C. M., & Lee, M. K. (2012). What drives consumers to spread electronic word of mouth in online consumer-opinion platforms. *Decision Support Systems, 53*(1), 218–225.
36. Qiu, L., Pang, J., & Lim, K. H. (2012). Effects of conflicting aggregated rating on eWOM review credibility and diagnosticity: The moderating role of review valence. *Decision Support Systems, 54*(1), 631–643.
37. Jiang, Z., & Benbasat, I. (2004). Virtual product experience: Effects of visual and functional control of products on perceived diagnosticity and flow in electronic shopping. *Journal of Management Information Systems, 21*(3), 111–147.
38. Pavlou, P. A., Liang, H., & Xue, Y. (2007). Understanding and mitigating uncertainty in online exchange relationships: A principal-agent perspective. *MIS Quarterly, 31*(1), 105–136.
39. Cao, Q., Duan, W., & Gan, Q. (2011). Exploring determinants of voting for the "helpfulness" of online user reviews: A text mining approach. *Decision Support Systems, 50*(2), 511–521.
40. Ghose, A., & Ipeirotis, P. G. (2011). Estimating the helpfulness and economic impact of product reviews: Mining text and reviewer characteristics. *IEEE Transactions on Knowledge and Data Engineering, 23*(10), 1498–1512.
41. Korfiatis, N., García-Bariocanal, E., & Sánchez-Alonso, S. (2012). Evaluating content quality and helpfulness of online product reviews: The interplay of review helpfulness vs. review content. *Electronic Commerce Research and Applications, 11*(3), 205–217.
42. Sweeney, J. C., Soutar, G. N., & Mazzarol, T. (2012). Word of mouth: measuring the power of individual messages. *European Journal of Marketing, 46*(1/2), 237–257.
43. Lin, T. M., Lu, K., & Wu, J. (2012). The effects of visual information in eWOM communication. *Journal of Research in Interactive Marketing, 6*(1), 7–26.
44. Chevalier, J. A., & Mayzlin, D. (2006). The effect of word of mouth on sales: Online book reviews. *Journal of Marketing Research, 43*(3), 345–354.
45. Wilson, E. J., & Sherrell, D. L. (1993). Source effects in communication and persuasion research: A meta-analysis of effect size. *Journal of the Academy of Marketing Science, 21*(2), 101–112.
46. Filieri, R., & McLeay, F. (2014). E-WOM and accommodation: An analysis of the factors that influence travelers' adoption of information from online reviews. *Journal of Travel Research, 53*(1), 44–57.
47. Dichter, E. (1966). How word-of-mouth advertising works? *Harvard Business Review, 44*(6), 147–166.
48. Balasubramanian, S., & Mahajan, V. (2001). The economic leverage of the virtual community. *International Journal of Electronic Commerce, 5*(3), 103–138.
49. Sundaram, D. S., Mitra, K., & Webster, C. (1998). Word-of-mouth communications: A motivational analysis. *Advances in Consumer Research, 25*(1), 527–531.
50. Picazo-Vela, S., Chou, S. Y., Melcher, A. J., & Pearson, J. M. (2010). Why provide an online review? An extended theory of planned behavior and the role of big-five personality traits. *Computers in Human Behavior, 26*(4), 685–696.
51. Ridgeway, C. L., & Walker, H. A. (1995). Status structures. In K. S. Cook, G. A. Fine, & J. S. House (Eds.), *Sociological perspectives on social psychology* (pp. 281–310). Boston: Allyn & Bacon.
52. Lampel, J., & Bhalla, A. (2007). The role of status seeking in online communities: Giving the gift of experience. *Journal of Computer-Mediated Communication, 12*(2), 434–455.
53. Weber, M. (1968). *Economy and society: An outline of interpretive sociology*. New York: Bedminister Press.
54. Frank, R. H. (1984). Interdependent preferences and the competitive wage structure. *The Rand Journal of Economics, 15*(4), 510–520.
55. Berger, J., Cohen, B. P., & Zelditch, M., Jr. (1972). Status characteristics and social interaction. *American Sociological Review, 37*(3), 241–255.
56. Thye, S. R. (2000). A status value theory of power in exchange relations. *American Sociological Review, 65*(3), 407–432.
57. Washington, M., & Zajac, E. J. (2005). Status evolution and competition: Theory and evidence. *Academy of Management Journal, 48*(2), 282–296.

58. Ball, S. B., & Eckel, C. C. (1996). Buying status: Experimental evidence on status in negotiation. *Psychology & Marketing, 13*(4), 381–405.
59. Gerber, G. L. (1996). Status in same-gender and mixed-gender police dyads: Effects on personality attributions. *Social Psychology Quarterly, 59*(4), 350–363.
60. Huberman, B. A., Loch, C. H., & Önçüler, A. (2004). Status as a valued resource. *Social Psychology Quarterly, 67*(1), 103–114.
61. Fisek, M. H., Conner, T. L., & Berger, J. (1983). *Expectation states theory: A theoretical research program*. Lanham: University Press of America.
62. Tobias, M., & Dennis, K. (2014). Don't take away my status!—Evidence from the restructuring of a virtual reward system. *Computer Networks, 75*(12), 477–490.
63. Zhang, X., & Wang, C. (2012). Network positions and contributions to online public goods: The case of Chinese Wikipedia. *Journal of Management Information Systems, 29*(2), 11–40.
64. Heyman, J., & Ariely, D. (2004). Effort for payment a tale of two markets. *Psychological Science, 15*(11), 787–793.
65. Ariely, D., Bracha, A., & Meier, S. (2009). Doing good or doing well? Image motivation and monetary incentives in behaving prosocially. *American Economic Review, 99*(1), 544–555.
66. Zhang, X., & Zhu, F. (2011). Group size and incentives to contribute: A natural experiment at Chinese Wikipedia. *American Economic Review, 101*(4), 1601–1615.
67. Burtch, G., Hong, Y., Bapna, R., & Griskevicius, V. (2016). Stimulating online reviews by combining financial incentives and social norms. *Management Science*. doi:10.1287/mnsc.2016.2715.
68. Krosnick, J. A., Boninger, D. S., Chuang, Y. C., Berent, M. K., & Carnot, C. G. (1993). Attitude strength: One construct or many related constructs? *Journal of Personality and Social Psychology, 65*(6), 1132.
69. Casaló, L. V., Flavián, C., & Guinalíu, M. (2008). The role of satisfaction and website usability in developing customer loyalty and positive word-of-mouth in the e-banking services. *International Journal of Bank Marketing, 26*(6), 399–417.
70. de Matos, C. A., & Rossi, C. A. V. (2008). Word-of-mouth communications in marketing: A meta-analytic review of the antecedents and moderators. *Journal of the Academy of Marketing Science, 36*(4), 578–596.
71. Zeelenberg, M., & Pieters, R. (2004). Beyond valence in customer dissatisfaction: A review and new findings on behavioral responses to regret and disappointment in failed services. *Journal of Business Research, 57*(4), 445–455.
72. Pan, Y., & Zhang, J. Q. (2011). Born unequal: A study of the helpfulness of user-generated product reviews. *Journal of Retailing, 87*(4), 598–612.
73. Bazerman, M. H., Loewenstein, G. F., & White, S. B. (1992). Reversals of preference in allocation decisions: Judging an alternative versus choosing among alternatives. *Administrative Science Quarterly, 37*(2), 220–240.
74. Skowronski, J. J., & Carlston, D. E. (1989). Negativity and extremity biases in impression formation: A review of explanations. *Psychological Bulletin, 105*(1), 131–142.
75. Herr, P. M., Kardes, F. R., & Kim, J. (1991). Effects of word-of-mouth and product-attribute information on persuasion: An accessibility-diagnosticity perspective. *Journal of Consumer Research, 17*(4), 454–462.
76. Ballou, D. P., & Pazer, H. L. (1985). Modeling data and process quality in multi-input, multi-output information systems. *Management Science, 31*(2), 150–162.
77. Nelson, R. R., Todd, P. A., & Wixom, B. H. (2005). Antecedents of information and system quality: An empirical examination within the context of data warehousing. *Journal of Management Information Systems, 21*(4), 199–235.
78. Hovland, C. I., Janis, I. L., & Kelley, H. H. (1953). *Communication and persuasion; psychological studies of opinion change*. New Haven, CT, US: Yale University Press.
79. Hovland, C. I., & Weiss, W. (1951). The influence of source credibility on communication effectiveness. *The Public Opinion Quarterly, 15*(4), 635–650.
80. Connors, L., Mudambi, S. M., & Schuff, D. (2011). *Is it the review or the reviewer? A multi-method approach to determine the antecedents of online review helpfulness*. Hawaii: IEEE.
81. Bailey, A. A. (2005). Consumer awareness and use of product review websites. *Journal of Interactive Advertising, 6*(1), 90–108.
82. Hu, N., Liu, L., & Zhang, J. J. (2008). Do online reviews affect product sales? The role of reviewer characteristics and temporal effects. *Information Technology and Management, 9*(3), 201–214.

83. Weathers, D., Sharma, S., & Wood, S. L. (2007). Effects of online communication practices on consumer perceptions of performance uncertainty for search and experience goods. *Journal of Retailing, 83*(4), 393–401.
84. Nelson, P. (1970). Information and consumer behavior. *The Journal of Political Economy, 78*(2), 311–329.
85. Nelson, P. (1974). Advertising as information. *The Journal of Political Economy, 82*(4), 729–754.
86. Huang, P., Lurie, N. H., & Mitra, S. (2009). Searching for experience on the web: An empirical examination of consumer behavior for search and experience goods. *Journal of Marketing, 73*(2), 55–69.
87. Bei, L. T., Chen, E. Y. I., & Widdows, R. (2004). Consumers' online information search behavior and the phenomenon of search vs. experience products. *Journal of Family and Economic Issues, 25*(4), 449–467.
88. Jiang, P. (2004). The role of brand name in customization decisions: A search vs experience perspective. *Journal of Product & Brand Management, 13*(2), 73–83.
89. Cao, Y., Gruca, T. S., & Klemz, B. R. (2003). Internet pricing, price satisfaction, and customer satisfaction. *International Journal of Electronic Commerce, 8*(2), 31–50.
90. Duan, W., Gu, B., & Whinston, A. B. (2008). Do online reviews matter?—An empirical investigation of panel data. *Decision Support Systems, 45*(4), 1007–1016.
91. Sun, M. (2012). How does the variance of product ratings matter? *Management Science, 58*(4), 696–707.
92. Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. *Behavior Research Methods, 40*(3), 879–891.
93. Hayes, A. F. (2012). PROCESS: A versatile computational tool for observed variable mediation, moderation, and conditional process modeling. Retrieved from http://www.afhayes.com/public/process2012.pdf.
94. Hong, Y., & Pavlou, P. A. (2014). Product fit uncertainty in online markets: Nature effects, and antecedents. *Information Systems Research, 25*(2), 328–344.
95. Diehl, K., & Poynor, C. (2010). Great expectations?! Assortment size, expectations, and satisfaction. *Journal of Marketing Research, 47*(2), 312–322.