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ORIGINAL ARTICLE

Who will stay with the brand after posting non-5/5 rating of purchase? An empirical study of online consumer repurchase behavior

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Abstract

Customer retention has been fully examined in marketing research. It has been noticed that satisfied customers do not always retain and customer churn happens repeatedly in an e-Business context. In this paper, we focus on online consumer repurchase behavior on online business to consumer platforms after posting a non-5/5 rating of the purchased product. The non-5/5 rating can be taken as buyer's self-claimed non-fully satisfaction on shopping experience. We investigate whether online consumers' self-claimed non-fully satisfied shopping experience of a brand would attenuate their repurchase intention of the same brand, and further, what factors would impact their repurchase frequency and the time interval to the next purchase of this brand. We applied multinomial logit regression and ordinary least square regressions to Amazon review data to test the research hypotheses. We collected more than 241 thousand review records involving over 182 thousand buyers of Amazon beauty products. 44% of these buyers rated below 5, and 19% out of whom had repurchase records. The empirical results showed that consumers' past shopping experience and the non-5/5 rating level significantly impact the possibility of repurchase intention; consumers' emotional stability is associated with their repurchase frequency positively; their relationship proneness to a certain brand shortens the time interval to the next purchase of the brand. Managerial implications and future research directions are discussed last.

Keywords Customer retention · Customer dissatisfaction · Online repurchase behavior · Multinomial logit regression · Online reviews

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1 Introduction

In academia, consumer repurchase behavior has gained adequate attention in recent years. The importance of customer retention has been fully examined in marketing research as a key to increase customer value and reduce firms' costs (Abdolvand et al. 2015). Xevelonakis (2005) stated that customer retention is profitable for a firm. Payne and Holt (2001) verified that exchanges with existing customers leads to higher profitability. Gupta et al. (2006) demonstrated that a small percentage increase in retention rate could bring up a high percentage increase in profitability. In prior research, customer retention has been regarded as an important index to evaluate customer lifetime value (CLV), a long-time customer profitability metric (Haenlein et al. 2006), referring to the net present value contributed by a customer to a firm (Abdolvand et al. 2015). Gupta et al. (2006) illustrated that customer retention rate is positively associated with CLV. Tsai et al. (2013) claimed that customer retention rate reflects financial return between a customer and a firm based on their relationship.

Since the cost of customer retention is far less than that of new customer acquisition, attaining customer retention is critical for achieving customer lifetime value. In other words, decreasing customer churn rate is crucial for a firm to increase customer lifetime value. Researchers paid more attention to three aspects: reasons of customer churn, internal mechanisms of customer loss, and reduction of customer churn. Prior research found that dissatisfaction is a driver of customer churn rate. Various service encounters, such as price, speed of delivery, and courtesy, have been confirmed to lead to customer dissatisfaction, which easily results in customer churn in the logistics industry (Chen et al. 2015). Kumar et al. (2018) developed a "mixture cure-competing risks" model, explaining multiple reasons for customer churn rate, customer dissatisfaction included. Hansen et al. (2013) found that customer churn rate decreases with satisfaction and increases with prior churn.

Given that an abundance of research noticed the direct influence of customer dissatisfaction on customer churn rate, there are a few cases that indicate that unsatisfied customers do not change their repurchase intention. For example, a switching barrier, such as technological switching, cost, and long term interorganizational relationship makes a firm difficult to change their intention with existing partners (Jones et al. 2000). Moreover, brand preference plays an important role in customer repurchase intention. Haverila and Haverila (2015) mentioned that brand value has a positive influence on the relationship between customer satisfaction and repurchase intention.

In the rapidly developed business environment that we see today, customer purchase channels become diversified, and monetary switching cost has decreased rapidly. Therefore, customers tend to churn repeatedly (Griffin and Lowenstein2002), but customer churn may not be "dead opportunities" any longer. In fact, satisfied customers do not always retain, and unsatisfied customers do not always switch to another brand. In the e-Business era, the impact of switching barriers on online consumers has been mitigated. Some conclusions and mechanisms of prior research in traditional industry may not be adapted exactly to online scenarios, and some research models may not be fully effective to explain online purchase and repurchase behavior (Khalifa and Liu 2007). Thus, online consumer repurchase behavior is worth investigation for online retailers and e-Business platforms to create long-term business value.

This paper examines how an unpleasant online experience impacts consumers' repurchase behavior. As for online consumers, their brand switch costs decrease dramatically. Thus, how to achieve online consumer retention especially after he/she has an imperfect experience is of great value. Amazon is the largest online retailer in the world. Amazon users can evaluate their purchased products after delivery. A non-5/5 rating can be interpreted as a self-claimed non-fully perfect or non-fully satisfied shopping experience. We examine the non-fully satisfied or non-fully pleasant Amazon users' repurchase behavior. Concretely, the research questions of this paper are: after a non-5/5 rating shopping experience,

1. Whether a consumer after non-5/5 rating posting would repurchase the same brand in the future and what factors impacts his/her behavior?
2. If the consumer after non-5/5 rating posting does not churn, what factors impacts his/her repurchase frequency of the same brand?
3. If the consumer after non-5/5 rating posting does not churn, what factors impact his/her repurchase time interval of the same brand?

The rest of the article is organized as follows. We provide an overview of relevant research on customer retention and online review followed by related theoretical background to propose our research hypotheses. Then, we introduce the econometrical model and data sources in detail for empirical analysis. We next present the empirical results of our analysis and discuss them. Finally, we provide managerial implications for practice, the limitations of this article, and recommend directions for future research.

2 Related literature

This paper explores online repurchase behavior especially of those who have experienced imperfect shopping. We identify these self-claimed non-fully satisfied consumers from product evaluations of a non-5/5 rating from Amazon review data. Thus, in this section we sum up two literature streams: related literature on customer retention and the factors impacting customer retention rate; and an extensive review of research on online reviews and its affiliation to other marketing mix.

2.1 Customer retention

Customer retention has been examined considerably in academia as an important part in marketing performance outcomes because it contains a lot of information about customer behaviors, which can affect company sales (Katsikeas et al. 2016).

Dastane and Fazlin (2017) claimed that the cost of acquiring new customers is higher than that of striving for retaining customers. Therefore, customer retention leads to cost savings, profitability, and relationship strengthening, as a result of lowering retained customers' price sensitivity and increasing the possibility of referring new customers. Moreover, Scherer et al. (2015) mentioned that creating value for customers and managing customers' co-creation of value should be taken into consideration strategically for the firm. All in all, customer retention has become one of the firms' critical success factors for diversified industrial markets as well as the huge consumer market.

How to achieve customer retention has been considerably examined in prior research. Rust and Zahorik (1993) stated that customer satisfaction could push up repurchase in various industrial and social contexts. Accordingly, Levesque and McDougall (1996) found that customer dissatisfaction eliminates an organization's customer base and erodes a corporation's reputation without ensuring customer retention. Kumar et al. (2017) believed firms' continuous evaluation of the provision of customer services can bring competitive advantages for themselves. Furthermore, the drivers of customer retention include brand value, service provider reputation, trust, and so on. In particular, trust as an important key factor has a positive impact on customer retention (Milan et al. 2015).

Pricing strategies have been attributed as potential issues to customer repurchase behavior as well. Chen et al. (2015) found that the attributes of price and discounts significantly influence likelihood of customer retention. However, Papatla and Krishnamurthi (1996) demonstrated empirically that initial discounts negatively affect customer retention mainly because customers can be more sensitive to prices with discounts. Freimer and Dan (2008) claimed that initial discounts have a positive influence on repurchase behavior, customer habit building, and loyalty. Olivares et al. (2018) confirmed that a moderate discount is necessary for customer retention since it indirectly achieves customer retention when consumers' purchase habits exist (Murray and Häubl 2007). Pauwels et al. (2002) pointed out that when customers adapt to discounts and build up positive purchase habits, after the discount period expires, the likelihood of repurchase behavior can be strengthened.

Research on relationship marketing has verified that customer relationship benefits customer retention to the brand (Bolton 1998). Krautz and Hoffmann (2017) predicted the mechanism among customer segmentation (based on past purchase history), the relationship tenure and two attitudinal customer variables, and their cross-cultural impact on customer retention. Further, research found that customer retention rate differs across product categories. Park and Han (2013) examined the relationship between customer retention rates and product diversity for online retailers, illustrating that diversified product categories increase consumer repurchase intention. Instead, Estelami and Maeyer (2004) found that the next purchase decision for durable consumer goods is always far from a customer's last purchase, which urges firms to maintain good relationships with existing customers.

Other strategies such as multi-channels accelerate a firm to attain customer retention as well. Scherer et al. (2015) found that technology-based self-service in addition to traditional personal service in the service sector enables the firm to increase customer retention rates in the long run and works more profitably and efficiently than any single channel respectively.

Switching cost across purchasing channels is a factor to be reckoned for customers to make repurchase decisions, which split the customers to retain or to churn at the presence of various brands. Besides the high switching cost of industrial markets, shopping habits and experiences coinstantaneous add up to switching cost when a consumer is about to churn and turn to a new brand in the consumer market. Khalifa and Liu (2007) proved that online shopping habits and online shopping experiences have a positive impact on customer retention rate since the customers are hesitant to switch at the cost of information searching and risk taking of an unfamiliar product.

This paper aims to examine the online repurchase behavior, concretely the repurchase intentions, the time interval of repurchase, and the future repurchase frequency of the same brand, of those who have experienced online shopping with non-5/5 rating of purchase. Therefore, the summary of customer retention and its influencing factors contribute relevant references to the study in the online context.

2.2 Online reviews

Online consumers would like to comment and share about their online shopping experiences such as product/service quality, delivery efficacy, and the sellers' responsiveness, which are useful references for new comers to understand the products and make purchase decisions. Thus, online reviews have obtained great attention from researchers who have examined the review usefulness, helpfulness, its influence on other financial indexes, and the mechanisms behind consumer online purchase behavior.

Prior research has investigated online reviews from two primary perspectives. From the point of view of online retailers, many studies have demonstrated the significant effect of online reviews as a function of electronic word-of-mouth, on sales volume. E.g., Clemons et al. (2006) suggested that the variance of ratings and the strength of the most positive quartile of reviews are positively related to sales growth; Duan et al. (2008a, b) verified that box office sales are significantly increased by the volume of online postings. Other elements of online reviews such as reviewer disclosure of identity information (Forman et al. 2008), review valence (Ho-dac et al. 2013; Floh et al. 2013), Semantic content and style properties (Ludwig et al. 2013) are verified to have a significant positive influence on sales. In addition, research on online reviews helps firms bring forward marketing strategies. E.g., Chen and Xie (2005) stated that a firm could adopt a pricing strategy or advertising strategy based on the characteristics of product reviews. Moreover, several studies provided product improvement strategies according to the features of textual content of online reviews (e.g., Zhang et al. 2018; Qi et al. 2016). Most of the research on online reviews was done empirically, though Kwark et al. (2014) applied an analytical game theoretical model to explore the impact of online reviews left on the online retailer or the brands respectively according to the review content.

Another branch of research focuses on the underlying mechanisms of affecting other consumers' purchase behavior. These studies mainly explore the usefulness and helpfulness of online reviews to potential consumers. E.g., Yin et al. (2014) found that reviews containing content indicating anxiety are more helpful than those containing content indicative of anger; Hong et al. (2017) empirically confirmed that review depth, review age, reviewer information disclosure, and reviewer expertise all have positive influences on review helpfulness through a meta-analysis. Further review features such as specific review content and writing styles (e.g., Siering et al. 2018; Singh et al. 2017; Agnihotri and Bhattacharya 2016), review readability (Agnihotri and Bhattacharya 2016), and product rating and review valence (Yin et al. 2016) have been verified to have a positive impact on review helpfulness.

We sum up recent studies on online reviews and provide an overview in Table 1 below. Distinct from most research, which focuses on either the firm's or other consumer's angle of view, our study tracks the reviewer's repurchase behavior that brings insights for the online retailers and manufacturers to predict their online customer retention rates in turn and explore the impacting factors in this study.

3 Theoretical background and model development

This paper aims to examine the repurchase behavior of online consumers who post non-5/5 ratings. The higher rating (among 1, 2, 3, 4) means less unsatisfied the online consumer is. We explore whether the self-claimed non-fully satisfied consumer would repurchase the brand that disappointed him or her, and if so, what factors would impact his/her repurchase frequency in the future and time interval to the next purchase of this brand. Thus, in this section we put forward potential impacting factors regarding our research purposes and propose the research hypotheses.

3.1 Satisfaction

Satisfaction is defined by Oliver et al. (1997) as when the consumer senses that consumption fulfills some need, desire, goal, and this fulfillment is pleasurable. Oliver (1999) further points out that satisfaction is the consumer's sense that consumption provides outcomes against a standard of pleasure versus displeasure. Customer satisfaction has been regarded as a fundamental determinant of long-term consumer behavior (Oliver 1980; Yi 1990). The role satisfaction plays as a key driver for consumer's repurchase intention and behavior has been emphasized by a large number of researchers in various different industrial and social contexts (e.g., Oliver1999; Rust and Zahorik 1993; Rust et al. 1995).

Existing research has verified the effect of online shopping satisfaction on consumer's repurchase. Khalifa and Liu (2007) demonstrated that online shopping satisfaction has a significant positive effect on online repurchase intention. Fang et al. (2014) conducted an empirical study and emphasized the positive effect of satisfaction on online repurchase intention through trust.

Table 1 Overview of recent research on online review

References	Dependent variables	Independent variables	Major findings
Chen and Xie (2005)	Marketing strategies	Review text	Firms should choose advertising rather than price as a strategic variable in response to product reviews when enough consumers value horizontal product attributes
Clemons et al. (2006)	Sales growth	Variance of ratings, high-end ratings	The variance of ratings and the strength of the most positive quartile of reviews are positively related to sales growth
Chevalier and Mayzlin (2006)	Sales	Review valence	An incremental negative review is more powerful in decreasing book sales than an incremental positive review is in increasing sales
Duan et al. (2008a)	Box office sales	Number of reviews, review ratings	Box office sales are significantly influenced by the volume of online postings
Duan et al. (2008b)	Retail sales	Review valence, review volume	A movie's box office revenue and WOM valence significantly influence WOM volume. WOM volume in turn leads to higher box office performance
Forman et al. (2008)	Product sales	Reviewer disclosure of identity information	The prevalence of reviewer disclosure of identity information is associated with increases in subsequent online product sales
Mudambi and Schuf (2010)	Review helpfulness	Review extremity-star rating, review depth-word count	Effects of review extremity and review depth on review helpfulness are moderated by product type
Zhu and Zhang (2010)	Product sales	Online ratings, number of online reviews	Online reviews are more influential for less popular games and games whose players have greater Internet experience

Table 1 (continued)

References	Dependent variables	Independent variables	Major findings
Ho-dac et al. (2013)	Product sales	Review valence	Positive (negative) reviews increase (decrease) the sales of the weak brands but have no significant impact on the sales of the strong brands
Floh et al. (2013)	Purchase intention, paying willingness	Valence intensity	The valence intensity of online reviews moderates the effect of online reviews on purchase intentions
Ludwig et al. (2013)	Conversion rate	Semantic content, style properties	Positive changes in affective cues and increasing congruence with the product interest group's typical linguistic style directly and conjointly increase conversion rates
Huang et al. (2013)	Intention to accept reviews	Review content (attribute-based and experience-based)	Attribute-based reviews describing a search product and experience-based reviews describing an experience product lead to higher acceptance
Kwark et al. (2014)	Upstream competition	Quality information and Fit information of reviews	Quality information benefits the retailer but hurts the manufacturers while Fit information hurts the retailer but benefits the manufacturers
Yin et al. (2014)	Review helpfulness	Emotion type (anxiety vs. anger)	Reviews containing content indicative of anxiety are more helpful than those containing content indicative of anger
Tang et al. (2014)	Product sales	Review valence (Mixed-neutral UGC)	Mixed-neutral UGC amplifies the effects of positive and negative UGC on product sales whereas indifferent-neutral UGC attenuates them

Table 1 (continued)

References	Dependent variables	Independent variables	Major findings
Wang et al. (2015)	Product Sales	User reviews variance, critic reviews variance	Overall effects of user review variance can be negative, insignificant, or even positive: customer breadth and depth effects
Moore (2015)	Review helpfulness	Explanation type	Explained actions are more helpful for utilitarian products and explained reactions are more helpful for hedonic products
Yin et al. (2016)	Review helpfulness	Product ratings, review valence	Confirmation bias leads to greater perceived helpfulness for positive reviews (positivity effect) when the average product rating is high and for negative reviews (negativity effect) when the average product rating is low
Agnihotri and Bhattacharya (2016)	Review helpfulness	Review readability, sentimental tone	Lucid and sentimental reviews diminish in utility
Folse et al. (2016)	Review helpfulness, product attitude	NVEE (e.g., intense language, exclamation points, emoticons)	NVEE (negatively valence emotional expressions) use directly promotes review helpfulness and damages attitude toward the product when used by experts
Qi et al. (2016)	Product development	Review text	Text content of online reviews to product improvement
Kolomiiets et al. (2016)	Purchase and recommendation intention	Review wrap	Wrapping influences behavioral intentions in the direction of the valence of the first and last review read
Zhou and Duan (2016)	Software download	Review rating	A higher professional rating not only directly promotes software download but also results in more active user-generated WOM interactions, which indirectly lead to more downloads

Table 1 (continued)

References	Dependent variables	Independent variables	Major findings
Liu and Karahanna (2017)	Attribute preferences	Attribute-level performance, and its relationship between the overall numeric rating	Attribute preferences are influenced more by these online review characteristics than by the relevance of the attributes to the consumers' decision context
Nan et al. (2017)	Product rank, purchase	Product uncertainty (review text)	The lower the product uncertainty computed by many reviews, the higher the product rank, and the more likely consumers are to purchase the product
Karimi and Wang (2017)	Review helpfulness	A photo/image displayed next to the reviewer name	Reviewer profile image can significantly enhance consumer's evaluation of review helpfulness
Yin et al. (2017)	Review helpfulness	Expressed arousal (review text)	The marginal effect of arousal on perceived helpfulness is positive at low levels of arousal but diminishes at higher levels
Hong et al. (2017)	Review helpfulness	Review depth, review age, reviewer information disclosure, reviewer expertise	Review depth, review age, reviewer information disclosure, and reviewer expertise have positive influences on review helpfulness
Fan et al. (2017)	Product sales	Review text	The combination of the Bass model and the Norton model and sentiment analysis has higher forecasting accuracy
Singh et al. (2017)	Review helpfulness	Textual features such as popularity, subjectivity, entropy, and reading ease	The textual features such as readability, polarity, subjectivity, entropy, and the average review rating of the product over time are the most important parameters for helpfulness

Table 1 (continued)

References	Dependent variables	Independent variables	Major findings
Zhou et al. (2018)	Product performance	Online customer review volume	Review volume has a curvilinear relationship with customer agility, agility has a curvilinear relationship with product performance
Zhang et al. (2018)	Product improvement	Feature satisfaction, feature attention	The correlation between the change in the degree of feature satisfaction and product improvement is stronger than that between the change in the degree of feature attention and product improvement
Pelsmacker et al. (2018)	Review impression, positive WOM intention	Text valence, star rating and rated usefulness of online reviews	The influence of review text valence on evaluative responses is stronger for more highly involved people and for people who are more susceptible to interpersonal influence. The influence of rated review usefulness on review impression is marginally stronger for people who are more susceptible to interpersonal influence
Siering et al. (2018)	Review helpfulness	Review content-related signals, reviewer-related signals	Review content-related signals (specific review content and writing styles) and reviewer-related signals (reviewer expertise and non-anonymity) both influence review helpfulness
Fink et al. (2018)	Sales	Review length	Review length has a negative curvilinear (inverted-U-shaped) relationship with product demand

In consideration of brand preference, researchers have confirmed that higher online brand satisfaction leads to higher repurchase probability of the purchased brand in various industries such as banking (Ong et al. 2017), clothing (Tsai et al. 2016), and cell phones (Haverila and Haverila 2015).

In this study, we investigate whether the buyer's self-claimed non-fully satisfaction on shopping experience would hurt the consumer in particular. We define the self-claimed non-fully satisfied consumer as those whose rating is below score 5 (ranging from 1 to 4) of the purchased brand, where a relatively higher score represents less self-claimed non-fully satisfaction.

Therefore, according to above statements, we propose our hypotheses as follows:

H1a After posting non-5/5 rating of purchase, the less self-claimed non-fully satisfied the online consumer (the higher rating score) is, the higher possibility he/she would repurchase the same brand in the future.

H1b After posting non-5/5 rating of purchase, the less self-claimed non-fully satisfied the online consumer (the higher rating score) is, the higher is the repurchase frequency for the same brand in the future.

Consumer satisfaction facilitates decisions to make the next purchase. After a self-claimed non-fully satisfied shopping experience, the online consumer might churn and switch to the other brand when he/she has the demand for the consumable product again, which brings the risk of selecting another unfamiliar brand for him or her. The underlying switching cost becomes an impediment for the self-claimed non-fully satisfied consumer to churn and shift to another brand. Accordingly, the less self-claimed non-fully satisfied the online consumer is, the less time it will take to make the next purchase. Thus, we propose that:

H1c After posting non-5/5 rating of purchase, the less self-claimed non-fully satisfied the online consumer (the higher rating score) is, the shorter is the time interval to the next purchase of the same brand.

3.2 Online shopping experience

Researchers defined consumers' past online shopping experience as their prior shopping frequency and overall satisfaction of the past experience online (Yoon 2002). Prior research has demonstrated the mediating effect of prior frequency of online shopping experience on consumers' online shopping behavior. Dai et al. (2014) built a conceptual model to examine the influence of online shopping experience on perception of specific types of risks associated with online shopping and how each type of risk perception influences online purchase intentions. They found that consumers' previous online shopping experience is a strong positive predictor of online shoppers' purchase intentions for both non-digital and digital products. Yoon (2002) adopted consumer trust as mediation and verified that familiarity with e-commerce and prior satisfaction with e-commerce could saliently increase trust, which lead to higher intention to shop online. Since intentions play a directive role for volitional behavior (Bagozzi 1982), we could further conclude that past online shopping experience has a positive effect on online purchase behavior of a specific brand.

Some researchers meanwhile discussed the moderation effect of online shopping experience on the relationship of satisfaction and repurchase intention. Khalifa and Liu (2007) found that for the same level of satisfaction, higher experience leads to better accessibility (i.e., the speed of retrieving affect from memory) of the satisfaction in memory, strengthening the effect of satisfaction on repurchase intention. Contrarily, Pappas et al. (2014) argued that experience weakens the relationship of satisfaction and intention to repurchase in that low-experienced customers give more importance on the impact of increasing satisfaction on their future repurchase behavior while high-experienced users are mostly affected by other factors. Regardless of the contradictory results, neither of the research focused on repurchase behavior under the dissatisfaction scenario.

To understand the repurchase behavior of customers after posting non-5/5 rating, "inertia" additionally plays an important role in keeping the consumers from churning. Zeelenberg and Pieters (2004) defined inertia as the experienced absence of goal-directed behavior and incorporated it into the framework of customer behavior in response to dissatisfaction in a service context. White and Yanamandram (2007) explored the factors that may lead to customer retention after an unsatisfied shopping experience and emphasized the important role of inertia. In this study, those with more online shopping experience present higher inertia to stay and have a higher possibility to repurchase after a non-5/5 rating of purchase online.

Accordingly, online shopping experience with a certain brand increases brand familiarity (Alba and Hutchinson 1987), which is conceptualized as the number of brand-related direct or indirect experiences that have been accrued by the consumer (Park and Stoel 2005). Park and Stoel (2005) verified that brand familiarity reduces perceived risk of purchase and consequently leads to higher online purchase intention for that brand. Applying the "inertia" theory, we believe that higher brand familiarity results in higher consumer inertia, which leads to higher possibility to repurchase the same brand after a non-5/5 rating shopping experience. Thus, we propose that:

H2a After posting non-5/5 rating of purchase, the online consumer's past shopping experience is positively associated with the possibility of repurchase of the same brand in the future.

H2b After posting non-5/5 rating of purchase, the online consumer's past shopping experience is positively associated with the repurchase frequency of the same brand in the future.

Since more experienced online consumers are more familiar with the brand and are believed to have a higher intention to repurchase after a purchase with non-5/5 rating, and the "inertia" generated in consumers' past experience would push them to stay with their shopping habit, they spend less time to consider and search for alternative brands. Thus, we propose that:

H2c After posting non-5/5 rating of purchase, the online consumer's past shopping experience is negatively associated with the time interval to the next purchase of the same brand.

3.3 Emotional stability

Costa and McCrae (1992) described emotional stability as an alternative for neuroticism, which is one of the Big Five factors to categorize personality (Judge and Bono 2001; Celli and Rossi 2015). Given that the emotional system is a psychological system that can automatically maintain its equilibrium (Izard et al. 2000), emotional stability describes the efficiency of maintaining mood stability.

The emotional stability across time and over different situations (Cobb-Clark and Schurer 2012) has been demonstrated inherently in a strong relationship with human behavior (Kenny et al. 1992; Funder 1997). Specifically, most research in psychology has noted that emotional stability represents to what extent would one's negative emotions such as anxiety, depression, anger, worry be aroused (Judge and Bono 2001; Bove and Mitzifiris 2007; Celli and Rossi 2015; Li and Ahlstrom 2016). Emotional stability involves the conception of threshold. People whose scores are higher in emotional stability are those with a higher threshold of emotional response, which means one's negative emotions are more difficult to be activated (Judge and Bono 2001; Bove and Mitzifiris 2007; Li and Ahlstrom 2016).

Roos et al. (2009) claimed that customers with lower emotional stability tend to be angry and pessimistic about their service provider. That is to say, they would be more likely to post negative reviews when facing transaction failure of different degrees. On the other hand, Silva (2006) pointed out that emotionally stable people tend to be more committed. Al-hawari (2014) demonstrated that customers who are emotionally unstable are more akin to feel dissatisfaction and thus more inclined to switch to other brands compared to those with a more emotionally stable personality. This finding confirms the role of emotional stability to prevent customers from switching brands.

In this study, we adopt negative rating ratio to reflect emotional stability inversely. The negative rating ratio is expressed as the ration of the number of non-5/5 ratings given by an online consumer to the total number of ratings for all of his or her purchases, which represents the ratio of the self-claimed non-fully satisfied experiences to his or her total purchases. Negative rating ratio of an online consumer implicitly indicates his or her emotional stability, one of the personality traits, which reflects the general tendency of feeling self-claimed non-fully satisfied during his or her online purchase history. Concretely, a higher negative rating ratio of an online consumer indicates less emotional stability.

Based on the above arguments, we propose that:

H3a After posting non-5/5 rating of purchase, the lower an online consumer's emotional stability (the higher negative rating ratio) is, the lower is the repurchase frequency of the same brand in the future.

Li and Ahlstrom (2016) conclude that recovery time is another dimension of emotional stability. Recovery time is defined as the flexible adaptation to the changing demands of stressful experiences (Tugade and Fredrickson 2004). Applying self-organization theory, Li and Ahlstrom (2016) demonstrated that people with higher emotional stability need more time to cope with negative stimuli and restore the emotional system to a stable state.

Therefore, we surmise that after a self-claimed non-fully satisfied shopping with a certain brand, customers with a higher negative rating ratio (i.e., lower emotional stability) need less time to recover from the displeasure. In other words, there is a shorter time interval to repurchase the brand. Thus, we propose that:

H3b After posting non-5/5 rating of purchase, the lower an online consumer's emotional stability (the higher negative rating ratio) is, the shorter is the time interval to the next purchase of the same brand.

3.4 Relationship proneness

Consumer relationship proneness refers to a consumer's tendency to engage in long-term relationships with to a certain brand he/she used to purchase (Odekerken-Schroeder et al. 2003; Wulf et al. 2001). Customers differ in their willingness to establish relationships with their product or service providers, i.e., they are at a different level of relationship proneness, another important personality trait like emotional stability. Many researchers have underlined the important role of relationship proneness in contributing to consumer loyalty to businesses (e.g., Odekerken-Schroeder et al. 2003; Wulf et al. 2001; Hedrick et al. 2007; Vázquez-Carrasco and Foxall 2006).

We define an online consumer's relationship proneness as the division of total purchases of a brand by his/her total purchases in this study. In particular, we discuss consumer relationship proneness to the certain brand that dissatisfies the consumer who rates below a score of 5 for the first time during his/her online purchase experiences. Though most of the conclusions about relationship proneness were drawn in a generally positive situation, these results provide references for our research purposes in the case that the consumer was self-claimed non-fully satisfied with the brand.

Kim et al. (2012) claimed that for consumers with higher relationship proneness, quitting an existing relationship and rebuilding a new relationship could be difficult since they usually have a high level of resistance to change. Similarly, in online shopping scenarios, even after a non-5/5 rating purchase experience with a brand, customers with higher relationship proneness are more hesitant to switch, and thus are more likely to maintain the relationship. Thus, we propose that:

H4a After posting non-5/5 rating of purchase, the online consumer's relationship proneness is positively associated with the repurchase frequency of the same brand in the future.

In accordance with above arguments, online consumers with higher relationship proneness make the next purchase of the same brand faster than those with lower relationship proneness, since they are less hesitant to switch brands and have a lower possibility of swaying between alternative brands. Thus, we propose that:

H4b After posting non-5/5 rating of purchase, the online consumer's relationship proneness is negatively associated with the time interval to the next purchase of the same brand.

4 Methodologies and data analysis

In this section, we test our research hypotheses using econometric models. To be specific, we apply multinomial logit regression to test H1a and H2a, and apply OLS regression models to test the other hypotheses. We use a part of Amazon review data to apply to the econometric models for data analysis.

4.1 Data collection

Amazon review data is open to download upon request and has been utilized by academic researchers and machine learning engineers to examine the functions and features of recommendation systems (e.g., McAuley et al. 2015; He and McAuley 2016). Amazon review data contains great information of past transactions in the past few years. We use Amazon review data to apply our econometric models for data analysis. There are 24 categories of products on Amazon, such as books, electronics, movies and TV, clothing/shoes/jewelry, and the review data are provided per category. We analyze the online repurchase behavior to figure out whether a self-claimed non-fully satisfied shopping experience would hurt the consumer in the end.

According to the stated purpose of this study, we want to focus on a category so that the products belong to which satisfy (1) they are consumable physical products that consumers always have a need to repurchase; (2) they are needed by most families or individuals other than niche market; (3) they have been widely adopted through online channel. Therefore, we selected the "beauty" category since beauty products mostly include skincare, makeup, fragrance, oral care, all of which are non-durable products and needed by almost everyone and sold online as a major channel nowadays.

We extracted 2,023,070 review records added up to by review ID for beauty products before 2014 (after when the Amazon data is not open). Each record consists of the attributes including reviewer ID, product ID, product name, review text, rating, product category, brand name, review time. Since one record of the review data refers to one record of transaction, the review data can reflect the customer purchase behavior and their evaluation clearly if we group the data entries by reviewer ID.

The attribute rating represents the customer's evaluation for this purchase. Customers of Amazon are able to rate products on a five-star rating scale ranging from 1 = "I hate it" to 5 = "I love it" as defined by Engler et al. (2015); they developed a customer satisfaction model of online product ratings to explain the score of ratings by the dataset of Amazon. They suggested that customers' ratings of products depend on product expectations and performance. Therefore, if the rating is not 5 indicating a perfect shopping experience, there must be a discrepancy between customer's expectations and product performance. Therefore, we define a review score of less than 5 to be an unsatisfactory or imperfect purchase experience, since there must be a reason that accounted for a rating score other than 5, the best evaluation.

To explore whether the a self-claimed non-fully satisfied shopping experience impacts online consumers' brand preference, we selected the data set of beauty products and kept 241,113 records of review data from the top 20 beauty brands ranked by sales among the beauty category, which consisted of 182,624 Amazon buyers altogether. Table 2 summarizes the buyers from the 20 beauty brands ranked by sales and describes the proportion of each kind of buyers in detail.

Since the stated purpose of this study is to examine self-claimed non-fully satisfied consumers' repurchase behavior and explore the factors that affect customers' repurchase behavior after an unsatisfactory purchase experience, we filtered the review records by deleting the records of the reviewer IDs (equal to consumer identity on Amazon) who rated each of his or her purchases in the data set as 5/5. We got a total of 81,064 Amazon buyers who had at least once left a rating below 5. This group accounted for 44.39% of the buyer base. The considerable proportion of self-claimed non-fully satisfied buyers indicates that their repurchase behavior and the influencing factors are worth investigation.

Table 3 further summarizes the distribution of buyers' negative rating counts for those who have once rated below 5, namely self-claimed non-fully satisfied buyers on Amazon. Nearly 88% of the buyers have rated below 5 only once representing only one non-5/5 rating purchase experience and evaluation. Less than 1% of buyers have had non-5/5 ratings for more than five times according to his or her entire transaction records of top 20 beauty products on Amazon.

Table 2 Summary of Amazon buyers from top 20 beauty brands ranked by sales

Description	Count	% of total buyers
Total review records	241,113	–
Total buyers involved	182,624	100.00
Buyers having only one purchase record	161,390	88.37
Buyers of all 5 rating	101,560	55.61
Buyers having rating below 5	81,064	44.39
Buyers having rating below 5 with no repurchase record	66,050	36.17
Buyers having rating below 5 with repurchase record	15,014	8.22

Table 3 Summary statistics of self-claimed non-fully satisfied buyers' negative rating counts

Negative rating count	Count	% of total buyers
1	71,307	87.96
2	6681	8.24
3	1722	2.12
4	597	0.74
5	266	0.33
> 5	491	0.61
Total	81,064	100.00

4.2 Descriptive statistics

To measure the two dependent variables, the whole data set were regrouped by reviewer ID. In each group, all rating records left by the same reviewer are listed in chronological order. Since the reviewer could rate only after the purchase order is completed, we assume each rating record represents a consumer's purchase or repurchase record on Amazon, and the reviewer's rating record series illustrates the consumer's all purchase records.

Table 4 defines the variables in the econometric models. The frequency of the same brand repurchase after the first unsatisfactory purchase, *fre*, is measured as the count of rating records of the same brand as that of the earliest rating below 5 and after the earliest rating below 5 in the reviewer's rating record set. The repurchase time interval of the same brand after the first satisfactory purchase, *intls*,

Table 4 Variable descriptions

Variables	Descriptions and implications
intls	The repurchase time interval of the same brand after the first unsatisfactory purchase
fre	The frequency of the same brand repurchases after the first unsatisfactory purchase
stf	The satisfaction of the first unsatisfactory purchase
ose	The online shopping experience
nrr	The negative rating ratio
rp	The relationship proneness to the brand
total	The total purchase
un	The total unsatisfactory purchase
avr	The total rating average
var	The total rating variance
avrre	The rating average of the same brand after the first unsatisfactory purchase
varre	The rating variance of the same brand after the first unsatisfactory purchase
ts	The total purchase of the same brand
avrs	The total rating average of the same brand
vars	The total rating variance of the same brand

is measured as the time difference between the earliest rating record below 5 and the next rating record of the same brand as it in the reviewer's rating record set.

The independent variables in the econometric models are: satisfaction (*stf*), online shopping experience (*ose*), negative rating ratio (*nrr*), and relationship proneness (*rp*). We define the rating of the first unsatisfactory experience of the buyer as his or her satisfaction (*stf*), which is opposite of the dissatisfaction level. We define the purchase frequency of the same brand before his or her first unsatisfactory purchase as online shopping experience (*ose*). We divide the total unsatisfactory purchase (*un*) by the total purchase of a buyer as his or her negative rating ratio (*nrr*). Since consumer relationship proneness refers to a consumer's tendency to engage in long-term relationships, relationship proneness (*rp*) is calculated by dividing the total purchase of the same brand (*ts*) by the total purchase of a buyer, suggesting that the more a buyer purchases the brand, the greater he or she desires to establish a long-term relationship with the brand.

Table 5 is the summary statistics of all the variables. From Table 5, the count of *intls, avrre* and *varre* is 6604, represents the count of those who repurchase the same brand after a non-5/5 rating of purchase. According to Table 2, the count of those who rate below 5 and repurchase is 15,014. Thus, 44% of self-claimed non-fully satisfied consumers still repurchase the brand that dissatisfies them. The standard deviation and the variance of the *intls* (the repurchase time interval between the first unsatisfactory purchase and the next purchase of the same brand) is so large that it is subjected to logarithmic processing in the empirical model. Table 6 is correlation matrix of all the variables. From Table 6, we can exclude the risk of multicollinearity of the variables in the econometric models.

Table 5 Descriptive statistics of the variables

	Count	Mean	Max	Min	Sd	Variance
intls	6604	148.551	3270	0	317.192	100,610.7
fre	81,064	0.125	33	0	0.596	0.355
stf	81,064	2.795	4	1	1.196	1.430
ose	81,064	0.044	32	0	0.296	0.088
nrr	81,064	0.915	1	0.033	0.199	0.040
rp	81,064	0.908	1	0.013	0.213	0.046
total	81,064	1.519	149	1	1.755	3.080
un	81,064	1.208	53	1	0.876	0.768
avr	81,064	2.962	4.97	1	1.214	1.474
var	81,064	0.237	4	0	0.689	0.475
avrre	6604	3.862	5	1	1.236	1.527
varre	6604	0.158	4	0	0.530	0.281
ts	81,064	1.169	45	1	0.722	0.521
avrs	81,064	2.859	4.96	1	1.210	1.464
vars	81,064	0.089	4	0	0.430	0.185

Table 6 Correlation matrix of the variables

l	*intls*	*fre*	*stf*	*ose*	*nrr*	*rp*	*total*	*un*	*avr*	*var*	*avrre*	*varre*	*ts*	*avrs*	*vars*
intls	1														
fre	0.141	1													
stf	0.015	0.061	1												
ose	−0.003	0.224	0.048	1											
nrr	−0.055	−0.301	−0.088	−0.386	1										
rp	−0.257	−0.082	−0.066	−0.038	0.652	1									
total	0.205	0.554	0.067	0.317	−0.517	−0.562	1								
un	0.240	0.474	0.050	0.083	−0.153	−0.464	0.811	1							
avr	0.044	0.143	0.911	0.159	−0.407	−0.280	0.226	0.093	1						
var	0.071	0.188	−0.178	0.161	−0.600	−0.534	0.340	0.231	0.136	1					
avrre	0.013	0.074	0.283	0.111	−0.646	−0.017	0.065	−0.190	0.790	0.028	1				
varre	0.098	0.345	−0.028	0.054	−0.063	−0.067	0.219	0.238	−0.024	0.249	−0.091	1			
ts	0.115	0.917	0.070	0.595	−0.407	−0.083	0.587	0.425	0.184	0.221	0.107	0.305	1		
avrs	0.027	0.147	0.966	0.169	−0.213	−0.082	0.142	0.074	0.943	−0.070	0.847	−0.040	0.191	1	
vars	0.049	0.335	−0.100	0.314	−0.386	−0.070	0.265	0.173	0.101	0.553	0.159	0.293	0.406	0.098	1

4.3 Econometric models and empirical results

To answer the first research question, since the dependent variable is not a continuous variable but a multiple dummy variable describing if the customer repurchases or not, we are not able to use the ordinary least squares (OLS) estimation method. Instead, we utilize a multinomial logistic regression approach to estimate the probability of the repurchase behavior in this study. The basic logistic regression models the relationship between the categorical dependent variable and the explanatory variables. Further, multinomial logistic regression is a classification method that generalizes logistic regression to multiclass problems with more than two possible discrete outcomes (Darroch and Ratcliff 1972). It is a model used to predict the probabilities of the different possible outcomes of a categorically distributed dependent variable for which there are more than two categories.

4.3.1 Multinomial Logit Model

Suppose that the response variable y has the outcome categories ($y = j, j = 0, j = 1, j = 2$) with respective probability $P(y = j)$.

$$P(y = j) = \frac{\exp\left(\beta_0 + \sum_{i=1}^{n} \beta_i x_i\right)}{1 + \exp\left(\beta_0 + \sum_{i=1}^{n} \beta_i x_i\right)} \tag{1}$$

Generally, the category ($y = 0$) of largest sample size should be chosen as the base category (reference category), and the probability of each category will be compared to the probability of the base category. For categories ($j = 1, j = 2$), the probabilities of each category are as follows (Wedagama 2009). For the reference category:

$$P(y = 0) = \frac{1}{1 + \exp\left(\beta_0 + \sum_{i=1}^{n} \beta_i x_i\right)} \tag{2}$$

The multinomial logit regression equation can be expressed as:

$$\ln \frac{P(y = j)}{P(y = 0)} = \beta_0 + \sum_{i=1}^{n} \beta_i x_i \tag{3}$$

where $\mathrm{\beta_0}$ is the constant, $\mathrm{x_i (i = 1, i = 2, \ldots, i = n)}$ are the explanatory variables, $\mathrm{\beta_i (i = 1, i = 2, \ldots, i = n)}$ are the coefficients for the explanatory variables, and $\mathrm{\frac{P(y=j)}{P(y=0)}}$ is called related risk, which is the probability of each category with the first category as reference.

Equations (1)–(3) above expresses the logit (log odds) as a linear function of the explanatory variables. Therefore, Eq. (3) allows for the interpretation of the logit weights for variables in the same way as in linear regressions.

Model 1: Multinomial logit model to predict self-claimed non-fully satisfied consumer's repurchase probability

In this paper, we aim to predict the churn rate and the retention rate for a popular brand online. Whereas from the self-claimed non-fully satisfied online consumer's perspective, he/she has three possible behavioral patterns after a purchase experience with non-5/5 rating: stop shopping from the e-Retailer; stay with the e-Retailer but shift to another brand; stay with the e-Retailer and repurchase the same brand which he/she experienced a non-5/5 rating shopping. Therefore, the multinomial logit model (MNL) is developed to test the possibilities of the three behavioral patterns and to investigate how the independent variables impact the probability of consumer's repurchase behavior by estimating the unknown parameters of the factors.

The multinomial logit model is established as Eq. (4):

$$\ln \frac{P(y=j)}{P(y=0)} = \beta_0 + \beta_1 stf + \beta_2 ose + \beta_3 \mathrm{var} \tag{4}$$

We define y as a multiple dummy variable, supposing that if the buyer repurchases the same brand after the first unsatisfactory purchase, $y = 2$; if he repurchases another brand, $y = 1$; if no repurchase occurs, $y = 0$.

As a nonlinear regression approach, the Multinomial Logit model results report the regression coefficients and the relative risk ratio (*Rrr*) for each independent variable. The regression coefficients can only reflect the impact direction of the independent variables on the dependent variable with their positive or negative value. And *Rrr* reflects the changing degree of the probability of the dependent variable with the change of the independent variables.

Table 7 represents the summary statistic of the dependent variables. The figures indicate that the buyers without repurchasing after the first unsatisfactory purchase take up the largest share, 81% out of three kinds of buyers specifically. To verify the MNL, the largest sample size should be chosen as the base category, i.e., those buyers without repurchase.

Table 8 shows the data analysis results of the multinomial logit model. The model Pseudo R^2 0.20, indicates a significant model fit (Greene 2012). As shown in Table 8, all of the explanatory variables exhibit statistically significant coefficients in the Multinomial Logit model.

Since in the MNL model, the value of the coefficient has no practical significance, the relative risk ratio (*Rrr*) must be considered. The coefficients of *stf* (0.641*** and 0.642***) suggest that *stf* has a positive relationship with the probability of repurchase of both the same brand and another brand. That is, the higher

Table 7 Summary statistics of the dependent variable in MNL

Dependent variable (y)	Observations
If no repurchase after the first unsatisfactory purchase	66,050
If repurchase another brand after the first unsatisfactory purchase	8410
If repurchase the same brand after the first unsatisfactory purchase	6604
Total	81,064

Table 8 Empirical results of the multinomial logit model

Variable	Repurchase another brand		Repurchase the same brand	
	Coef. (SE)	Rrr. (SE)	Coef. (SE)	Rrr. (SE)
stf	0.641*** (0.015)	1.899*** (0.029)	0.642*** (0.018)	1.900*** (0.034)
ose	−0.447*** (0.066)	0.639*** (0.042)	0.455*** (0.035)	1.576*** (0.055)
var	2.090*** (0.041)	8.083*** (0.330)	1.945*** (0.041)	6.996*** (0.288)
Constant	−4.685*** (0.056)	0.009*** (0.001)	−4.892*** (0.065)	0.008*** (0.001)
Wald/LR chi2	5455.37	19,728.50	5455.37	19,728.50
Prob > chi2	0.000			
Pseudo R2	0.201			
Observations	81,064			
Log likelihood	−39,280.041			

Robust standard errors in parentheses

***$p < 0.001$

rating (less dissatisfaction) leads to the greater probability of repurchase behavior. The *Rrr* of the *stf* (1.899*** and 1.900***) are both more than 1, indicating that as the *stf* increases by 1, the probability of repurchase of another brand increases by 89.9% and the probability of repurchase of the same brand increases by 90%. Thus, Hypothesis *H1a* is supported.

The coefficients of *ose* (− 0.447*** and 0.455***) show respectively that the past experience of online shopping has a negative relationship with the probability of the repurchase of another brand, and a positive relationship with the probability of repurchase of the same brand. The *Rrr* of *ose* of repurchase of another brand is less than 1 (0.639***), indicating that as the *ose* increases by 1, the probabilities of repurchase of the other brand decreases by 63.9%. However, the *Rrr* of *ose* of repurchase of the same brand (1.576***) claims that as the *ose* increases by 1, the probability of repurchase of same brand increases by 57.6%. Thus, Hypothesis *H2a* is supported.

4.3.2 OLS regression models

The Ordinary Least Square (OLS) regression approach is used to investigate the factors that affect the time interval to the next purchase after a non-5/5 rating shopping and the repurchase frequency of the same brand thereafter. Since *repurchase frequency* is a numerical variable that describes the frequency of the customer's repurchase after the first unsatisfactory rating, we can directly use the linear regression model to test the relationship between the independent and dependent variables. This variable is calculated by counting the buyer's purchase records of the same brand after the first unsatisfactory rating based on the chronological order of his or her total records.

Model 2: Regression model to estimate self-claimed non-fully satisfied consumer's repurchase frequency

The OLS regression of model 2 is used for estimating the relationship between the explanatory variables and the repurchase frequency of the same brand. The linear regression model is expressed as the following Eq. (5):

$$fre = \gamma_0 + \gamma_1 stf + \gamma_2 ose + \gamma_3 nrr + \gamma_4 rp + \gamma_5 avrre + \gamma_6 \mathrm{varre} + \varepsilon_j \tag{5}$$

The results of the OLS regression of model 2 are shown in Table 9. The significant and positive coefficient of *stf* (0.0851***) shows that the satisfaction level of an online consumer has a positive effect on *fre*. In other words, the less self-claimed non-fully satisfied the consumer is, the more he/she would repurchase the same brand. Thus, *H1b* is supported.

The coefficient of *ose* (0.327**) is significant and positive, showing that the self-claimed non-fully satisfied consumer's online shopping experience affects his or her repurchase frequency positively. Thus, *H2b* is supported.

Similarly, the coefficient of *nrr* (− 0.673***) suggests that it has a negative and significant relationship with the repurchase frequency. It intuitively explains the positive association between a self-claimed non-fully satisfied consumer's emotional stability and his or her repurchase frequency of the brand. Thus, *H3a* is supported.

However, the coefficient of *rp* (0.136) does not indicate a significant relationship with the dependent variable, so *H4a* is not supported.

To address the multicollinearity issue, the variance inflation factor (VIF) results for their variables are reported. Variance inflation factor (VIF) is the ratio of variance, especially used in a model with multiple terms. It can quantify a model's multicollinearity in a regression analysis, considering the size of the VIF is the key to analyze the magnitude of multicollinearity. According to Kutner et al. (2004), the rule of thumb is that when $0 < \mathrm{VIF} < 10$, the multicollinearity of the model is normal, but when $\mathrm{VIF} > 10$, the multicollinearity is high and the regression analysis would be hard to accept.

As is shown in Table 10, the VIF of all variables in model 2 are far below 10, which means the multicollinearity issue is negligible. The mean VIF 1.47 is

Table 9 Empirical results of regression model to estimate repurchase frequency

variables	Coefficient (SE)
stf	0.0851*** (0.014)
ose	0.327** (0.124)
nrr	−0.673*** (0.162)
rp	0.136 (0.083)
avrre	−0.015 (0.0173)
varre	0.922*** (0.061)
Constant	1.465*** (0.137)
Observations	6604
R-squared	0.178

Robust standard errors in parentheses

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

Table 10 The VIF of the model 2

Variable	VIF	1/VIF
nrr	2.27	0.440
avrre	2.07	0.482
ose	1.15	0.869
rp	1.15	0.872
stf	1.11	0.899
varre	1.04	0.965
Mean VIF	1.47	

much less than 10, confirming that the OLS regression analysis is accepted and the results are valid.

Model 3: Regression model to estimate self-claimed non-fully satisfied consumer's repurchase time interval

Model 3 uses OLS regression to estimate the effects of *stf, ose, nrr* and *rp* on the self-claimed non-fully satisfied consumer's time interval of his or her repurchase. The *intls* is defined as the time interval between the first unsatisfactory purchase and the next purchase of the same brand based on the chronological order of one buyer's total records. Since the degree of dispersion of *intls* is very large, we need to apply logarithmic transformation to it to adapt to the regression model. The linear model could then be specified in Eq. (6) below:

$$\ln intls = \lambda_0 + \lambda_1 stf + \lambda_2 ose + \lambda_3 nrr + \lambda_4 rp + \lambda_5 ts + \lambda_6 avrs + \lambda_7 vars + \varepsilon_i \tag{6}$$

where λ_0 is constant, ln*intls* represents the logarithm of time interval of the same brand repurchase, *rp* is the relationship proneness and *nrr* is the negative rating ratio. And *ts, avrs* and *vars* are the control variables, representing the total purchase

Table 11 Empirical results of regression model to estimate repurchase time interval

Variables	ln *intls* Coefficient (SE)
stf	0.088 (0.049)
ose	−0.153*** (0.041)
nrr	0.392* (0.161)
rp	−1.191*** (0.113)
ts	0.085*** (0.015)
avrs	0.032 (0.063)
vars	0.098* (0.040)
Constant	4.632*** (0.250)
Observations	3375
R-squared	0.043

Robust standard errors in parentheses

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

records of the same brand, the average, and variance of all the rating records of the same brand respectively. Table 11 shows the OLS regression model results of the model 3.

The coefficient of *ose* λ_2 (− 0.153***) is significant and negative, which means that an increase in *ose* leads to a decrease in the time interval to repurchase the same brand. This result shows that the consumer's online shopping experience shortens the decision time to make the same brand repurchase. Thus, *H2c* is supported.

The coefficient of *nrr* λ_3 (0.392*) suggests that the *nrr* affect the time interval of the same brand repurchase positively and significantly. Accordingly, it means that the consumer's emotional stability is negatively associated with the time interval of the same brand repurchase. Thus, *H3b* is supported.

The coefficient of *rp* λ_4 (− 1.191***) is significant and negative, showing that the self-claimed non-fully satisfied consumer's relationship proneness has a negative effect on the interval of the same brand repurchase. Thus, *H4b* is supported.

However, the coefficient of *stf* λ_1 (0.088) does not indicate a significant relationship with the dependent variable, meaning the level of satisfaction does not have a significant impact. Thus, *H1c* is not supported.

Table 12 presents the VIF of Model 3, showing that the multicollinearity of model 3 is low. The VIF of all variables and mean VIF are far lower than 10, indicating the validity of Model 3.

5 Conclusions and discussions

This paper studies online repurchase behavior especially for those who have experienced imperfect shopping experience from e-Retailers. We have extensively reviewed the literature of customer retention and research on online reviews, and proposed our research model. We developed multinomial logit regression and OLS regression to predict online self-claimed non-fully satisfied consumers repurchase intentions and estimate the influencing factors of repurchase frequency and the time interval to the next purchase of the same brand. We extracted Amazon review data in the econometric models to test the research hypotheses, eight out of ten hypotheses were supported based on the empirical results.

Table 12 The VIF of the model 3

Variable	VIF	1/VIF
avrs	3.58	0.279
stf	3.15	0.318
nrr	2.31	0.433
vars	1.71	0.584
ose	1.61	0.621
ts	1.6	0.627
rp	1.11	0.898
Mean VIF	2.15	

5.1 Major findings

To test our research hypotheses, we adopted the multinomial logit model to test the relationship between the possibilities of three kinds of behavioral decisions and the explanatory variables, i.e., online shopping experience and consumer satisfaction. The empirical result of the multinomial logit model verifies our research hypotheses that both consumer satisfaction and their online shopping experience significantly increase the possibility of repurchase of the same brand, given an imperfect shopping experience occurred. These two factors are positively associated to the self-claimed non-fully satisfied consumer's repurchase frequency of the same brand, according to the results of OLS regression models. In addition, the consumer's emotional stability increases his or her future purchase of the brand that once dissatisfied him/her. The results of the second OLS regression demonstrated that the time interval to the next purchase of the same brand is influenced by the consumer's online shopping experience, emotional stability, and relationship proneness in a negative manner, i.e., these three factors expedites his or her repurchase of the same brand even after a non-5/5 rating shopping.

The hypothesis *H4a* was tested not significantly, which could be probably explained that in some cases a loyal consumer was hurt deeper when he/she encountered a shopping experience with non-5/5 rating. The hypothesis *H1c* was tested not significantly, which could be explained that once a consumer experienced an online shopping below his or her expectation, he/she becomes hesitant to make the next purchase decision promptly.

5.2 Theoretical contributions and managerial implications

The research hypotheses supported in this study coincide with the theories of customer retention and customer lifetime in traditional business. However, two out of ten hypotheses were not supported. It means that online retention rate not only lies in the customer relationship and the brand value, it is also subject to the trust to the e-Retailers.

This paper examines the repurchase behavior of those who have posted non-5/5 rating of their online shopping. The data records present that there is a significant portion of online consumers who have self-claimed non-fully satisfied shopping experience with non-5/5 rating and then stay in the online channel and probably repurchase the same brand. These "self-claimed non-fully satisfied consumers" in this research have contributed to the brand in terms of transaction records and emotional connections in the long run. Thus, to improve the loyalty program in the context of e-Business, online businesses could never give up the consumers with non-5/5 rating and should pay their attention to all the potentially loyal consumers to increase the brand value.

Moreover, empirical results of three econometric models show that it is quite possible to keep online retention rate by increasing brand loyalty. The Multinomial Logit regression classifies the online consumer behavioral intention into three directions, which reflects the retention rate of the brand and the churn rate of the brand, or churn rate of the e-Retailer (represented by a portion of consumers shift to another brand online). These results bring insight for the online businesses to improve their product and service quality to enhance their online channel performance and create long term business value with their loyal consumers.

5.3 Limitations and future research directions

This study applied multinomial logit model to investigate online customer repurchase behavior once the customer experienced a shopping with non-5/5 rating. Alternatively, it is a good way to adopt regression discontinuity design to analyze the trend of online consumers repurchase behavior after dissatisfied shopping experience. Regression discontinuity approach may explain the repurchase behavior from a broader angle of view and indicate the businesses how to work for the "self-claimed non-fully satisfied consumers".

This study only limited the data source to the beauty category of Amazon review data since we want to test the research hypotheses in a category of common, non-durable products that used to be purchased online. In the future studies, we may want to consider to test the hypotheses in all categories of product review data. Thus, fixed effects model can be added to include all categories of product reviews in data analysis. In a fixed effect model, we assume the category effects are fixed and the parameters are not random across categories, which is used to control unobserved heterogeneity and to verify the model generality. Thus, more underlying factors might be found to understand the behavioral characteristics of the "self-claimed non-fully satisfied" consumers.

This study identifies consumers' repurchase behavior by their rating records left on Amazon. However, a buy on Amazon does not necessarily leave comment or review for the purchased product, which means that we underestimated the repurchase intention and behavior in our empirical analysis. Moreover, prior research demonstrated that consumers' behavioral intention is prone to change with social media influencers or their peers. Therefore, it is a meaningful direction to control such external variables by including data set such as media coverage or search frequency in this research.

This study defines a self-claimed non-fully satisfied consumer based on his or her rating for the product purchased on Amazon. If he/she rates below the highest score 5/5, it means an imperfect shopping experience. We applied term frequency analysis merely to exclude the platform services as a major reason leading to consumer dissatisfaction. However, more extensive text mining techniques and sentiment analysis are needed to explore the internal mechanisms of online consumers' dissatisfaction and accordingly repurchase behavior. It is interesting to investigate what leads to consumer dissatisfaction and how to keep online customer retention rate given diversified beneath reasons. This would help online businesses to identify the occasionally "self-claimed non-fully satisfied" but de facto loyal consumers from malicious reviewers and to take effective post sales activities.

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