An Empirical Analysis of Brand Effects on Online Consumer Repurchase Behavior After Unsatisfied Experience

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Abstract. This paper examines the online repurchase behavior and customer's complaint particularly given the customer has experienced an unsatisfied shopping. We use Least Square Dummy Variable method to construct fixed-effects models and use text mining to analyze Amazon review data. The empirical results show there are brand effects on repurchase behavior after unsatisfied experience. It proves that brand is a crucial factor affecting online consumer repurchase behavior after unsatisfied experience. Transaction-specific satisfaction and overall satisfaction have different influences on repurchase behavior after unsatisfied experience. The opposite effects of these two factors reflect that different kind of satisfaction has different influence on repurchase behavior after unsatisfied experience. We find that after unsatisfied experience, the frequency of repurchase behavior on popular brand is less than that on unpopular brand. Customers prefer to repurchase unpopular brand after unsatisfied experience. This paper figures out that the factors influencing customers' repurchase behavior after unsatisfied experience are more related to product itself, but less to channel.

Keywords: Online repurchase behavior · Unsatisfied experience · Shannon's information theory · Fixed-effects model · Least Square Dummy Variable model

1 Introduction

Consumers' repurchase behavior is a key to a firm. It is one of the most significant factors influencing a firm's financial performance [1] since it ensures that the company's products are sold continuously and profitably. Generally, it is expensive to have lost customers to return, so a firm will do their best to discover customer dissatisfaction and make corresponding efforts to ensure their long-term relationship [2]. Therefore, it is crucial to study the behavior of customers after their unsatisfactory experiences [3].

Nowadays, consumers can not only purchase products through traditional channels, but can in many cases shop online [4, 5]. Logistic regression [3], autoregressive model [6] and SEM models [7] have been used to verify the factors influencing repurchase behavior, but these methods have missing variables, which in turn leads to omitted variable bias. However, there are few studies about customer repurchase behavior after unsatisfied experience. In fact, after customers feel unsatisfied in purchase procedure,

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they might still repurchase, which is revealed by online customers' ratings and purchase records. But few researchers consider the condition where customers suffer unsatisfied experience. Thus, whether brand can influence customers repurchase behavior after unsatisfied experience, or what factors can impact such behavior is what we are interested in. So the aim of this study is to find why customers repurchase a brand after unsatisfied experience and the research questions of this paper are:

(1) What factors can impact customers repurchase frequency of the same brand after unsatisfied experience?
(2) Which kind of brands do customers prefer to repurchase after unsatisfied experience?
(3) Why do customers repurchase these brands after unsatisfied experience?

We have obtained a large number of consumer repurchase records and reviews on Amazon's public database, and through data mining and data analysis, the existence of this phenomenon is preliminarily proved. In order to reduce the bias caused by omitted variables, we use fixed-effects models and control some related variables.

The structure of this paper is as follows: next chapter is the review of the literature on customer repurchase behavior. Then, we develop a framework of the determinants of online repurchase behavior after unsatisfied experience in online review contexts. Lastly we calculate and discuss the data analysis results.

2 Literature Review

2.1 Transaction-Specific Satisfaction

Customer satisfaction and related constructs are important to increase competition and marketing for a firm [8]. There are some theories and practice of customer satisfaction measurement [8]. According to Bitner and Hubbert [9], transaction-specific satisfaction refers to "the consumer's dis/satisfaction with a discrete service encounter." That is, consumers tend to comment on particular events of a transaction [10]. Some researchers make empirical investigation of transaction-specific satisfaction and overall satisfaction [9, 11, 12]. Jones and Suh [10] empirically investigate transaction-specific satisfaction, overall satisfaction and repurchase intentions and find that the two types of satisfaction can be distinguished from one another. Also, they find both types of satisfaction can be measured using the same scale, and transaction-specific satisfaction has an influence on repurchase intentions when overall satisfaction is controlled. Furthermore, Jones and Suh [10] show that the interaction between transaction-specific satisfaction and overall satisfaction has a negative effect on consumers' repurchase intentions, while in this model, the main effect on repurchase intentions of overall satisfaction is positive. Thus, we propose that:

H1: Transaction-specific satisfaction has a negative influence on customers' repurchase behavior after unsatisfied experience.

2.2 Overall Satisfaction

Mittal, Ross and Baldasare [13] find that overall satisfaction and attribute-level performance have separate and distinct effects on repurchase intentions. Previous research [14] shows that overall satisfaction and performance are related to repurchase behavior. Montoya-Weiss, Voss and Grewal [15] propose a conceptual model of the determinants of online channel use and overall satisfaction with the service provider. They find the service quality provided through both the online channel and the traditional channel affects customers' overall satisfaction. Some researchers [1, 16] find that higher levels of customer satisfaction rates result in higher levels of customer retention rates, which leads to the increase of customer repurchase behavior.

Even though customers have unsatisfied experiences, they will also repurchase if the service recovery is given to increase their overall satisfaction [3, 17], or if their families and friends persuade and convince them. Thus, repurchase behavior can exist after unsatisfied experience.

According to Bitner and Hubbert [9], overall satisfaction refers to "the consumer's overall dis/satisfaction with the organization based on all encounters and experiences with that particular organization". Jones and Suh [10] think customers view overall satisfaction as commenting on global impressions and general experiences with the firm. Thus, we propose that:

H2: Overall satisfaction has a positive influence on repurchase behavior after unsatisfied experience.

2.3 Purchase Experience

Pappas et al. [18] describe that experience is indispensable factor for successful customer retention. Liang and Huang [19] point out that high-experienced customers tend to continue shopping. Zhou et al. [20] find that experience affects positively customers' intention to purchase online. However, Dholakia and Zhao [21] show that experienced customers can be hardly satisfied since they obtain more information during the shopping process.

According to Shannon's information theory [22], each thing has two states. When it is in a certain state S1 for a long time, then the probability $P(S_1) = p_1$ of the next moment at S_1 is large (may be set 0.9), and the probability $P(S_2) = p_2$ in state S_2 is small ($p_2 = 0.1$). The amount of information that event S_1 brings to people is $I_1 = -\log(p_1) = 0.152$ (takes 2 as the base), and the amount of information of S_2 is $I_2 = -\log(p_2) = 3.322$. Obviously I_1 is much smaller than I_2. That is to say, when the next moment of this thing is still at S_1, it brings little information to customers, so its influence on them is very small. On the contrary, when it is at S_2, because of the huge amount of information, its influence is very large, so everyone will pay attention to this matter. Thus, before they feel unsatisfied with a brand, customers who keep purchasing this brand are in satisfied emotion all the time. But when they suffer unsatisfied experiences for the first time, they may be impressed dramatically by this experience according to Shannon's information theory. Therefore, these customers' repurchase behavior of the same brand may decrease. Thus, we propose that:

H3a: Customers' prior online purchase experience has an influence on their repurchase behavior after unsatisfied experience.

H3b: Customers' satisfied purchase experience before they suffer unsatisfied experiences has a negative influence on repurchase behavior after unsatisfied experience.

2.4 Brand

Another key determinant of repurchase intent is public brand image [23]. Public brand image has been proved to affect repurchase intent directly [23] and indirectly through customer satisfaction [24–26]. Also, some researchers find that the positive effect of public brand image on repurchase intent is stronger for women than for men [27]. Brand preference is an intervening factor between customer satisfaction and repurchase intention [28]. Thus, brand has an influence on repurchase behavior. Meanwhile, Hellier et al. [28] suggest a model and show that there are seven important factors influencing repurchase intention, namely, service quality, equity and value, customer satisfaction, past loyalty, expected switching cost and brand preference. In addition, brand preference mediates the relationship between customer satisfaction and repurchase intention [28].

H4: Brand has a significant influence on customer repurchase behavior after unsatisfied experience.

3 Methodology

3.1 Fixed-Effects Model

A fixed-effects model is a statistical model and its parameters are fixed or non-random quantities, different from random effects models and mixed models. Regression methods of fixed effects are used to analyze longitudinal data with repeated measures on both independent and dependent variables [29]. Fixed-effects model makes it possible to control variables that have not or cannot be measured. For nonexperimental data, how to statically control variables that cannot be observed is difficult, unlike experimental research. Generally, three regression methods can construct fixed-effects models, namely, Least Square Dummy Variable model (LSDV), first-differenced equation (FD) and covariance estimator (CE).

Allison [30] points out that the dummy variable approach works well for linear regression and Poisson regression. It is acknowledged that the distribution of consumer repurchase behavior is Poisson distribution. And the fixed-effects analysis of repeated event data is conveniently [30]. Thus, this paper chooses LSDV method to construct our models. The benefit of LSDV is that an estimate of individual heterogeneity can be obtained to truly detect whether the fixed-effects model is effective.

3.2 Least Square Dummy Variable Model

Fixed-effects methods are used for data in which the dependent variable is measured on an interval scale and is linearly dependent on a set of predictor variables [29]. There are a set of individuals ($i = 1, \ldots, N$), each of whom is measured at two or more points in time ($t = 1, \ldots, T$). The basic model is:

$$y_{it} = \alpha + \beta X_{it} + \gamma Z_{it} + \varepsilon_{it} \tag{1}$$

Where y_{it} is the dependent variable, α is a constant, β and γ are vectors of coefficients, ε_{it} is for each individual at each point in time, X_{it} are predictor variables, and Z_{it} are dummy variables (Table 1).

Table 1. Symbol

Symbol	Description	Type
tss	Transaction-specific satisfaction	Numerical
pe	Purchase experience	Dummy
frp	Frequency of repurchase behavior of the same brand after unsatisfied experience	Numerical
ftpb	Frequency of total purchase behavior of the same brand	Numerical
fue	Frequency of unsatisfied experience	Numerical
osat	Overall satisfaction	Numerical
osv	Overall satisfaction variance	Numerical
suev	Satisfaction after unsatisfied experience variance	Numerical
$Brand_{it}$	Brand dummy variable	Dummy

Thus, we suggest our model:
Model A:

$$frp_1 = \alpha_1 + \beta_1 ftpb + \beta_2 fue + \beta_3 tss + \beta_4 osat + \beta_5 pe + \beta_6 osv + \gamma_1 Brand_{it} + \varepsilon_{it} \tag{2}$$

Model B:

$$\begin{aligned} frp_2 = \alpha_2 + \beta_7 ftpb + \beta_8 fue + \beta_9 tss + \beta_{10} osat + \beta_{11} pe + \beta_{12} osv \\ + \beta_{13} suev + \gamma_2 Brand_{it} + \varepsilon_{it} \end{aligned} \tag{3}$$

3.3 Data Collection

We use online Amazon review data [31, 32] to test the research models. Based on the research of Kincade et al. [33], the relationship between product durability and the repurchase of the brand variable is not significant, so this study chooses beauty industry as the object and the time span of the data is from 2003 to 2014.

There are 241,974 reviews in this sample, in which 869 reviews have missing values, so we exclude flawed reviews. The reviews we used are given by 182,624 customers, so repurchase behavior exists among these customers. Statistically, 81,062 customers, nearly half of the total, give negative reviews and among these customers, 14,901 have repurchase behavior.

To study the effect of brand on repurchase behavior after unsatisfied experience, the sample consists of the reviews of top20 brands.

Furthermore, to find out the real reasons why customers complain when they suffer unsatisfied experiences, we use 774,255 reviews, of which the customer rating are below 5 stars (5 stars are the highest score, and 1 star is the lowest), which we define as bad reviews, to solve this problem through text mining.

4 Results and Discussions

4.1 Models and Analysis

In order to test our hypotheses, whether transaction-specific satisfaction (H1), overall satisfaction (H2), purchase experience (H3) and brand (H4) influence customer repurchase behavior after unsatisfied experience, we use Least Square Dummy Variable model (LSDV) to construct fixed-effects (FE) estimation. Two models are used in this paper, the basic one (Model A) and the extended one (Model B). These two models regard frequency of repurchase behavior after unsatisfied experience as the dependent variable, and transaction-specific satisfaction, overall satisfaction, purchase experience and brand dummy variables as the independent variables. Frequency of total purchase behavior, frequency of unsatisfied experience and overall satisfaction variance are control variables. These variables above are the same in the two models, but in model B, there is another control variable: satisfaction after unsatisfied purchase experience variance, which can demonstrates the influence of satisfaction in different time on repurchase behavior after unsatisfied experience.

Table 2. Models

Independent variable	Dependent variable		Hypothesis
	Repurchase behavior		
	Model 1	Model 2	
Constant	−1.3294***	−1.3253***	
	(0.0290)	(0.0290)	
Control variable			
ftpb	0.8353***	0.8351***	
	(0.0024)	(0.0024)	
fue	0.2328***	0.2327***	
	(0.0046)	(0.0046)	
osv	0.0499***	0.0438***	
	(0.0053)	(0.0056)	
suev		0.0216**	
		(0.0066)	

(*continued*)

Table 2. (*continued*)

Independent variable	Dependent variable		Hypothesis
Explanatory variable			
tss	−0.0461***	−0.0438***	H1
	(0.0067)	(0.0067)	
osat	0.1418***	0.1396***	H2
	(0.0079)	(0.0080)	
pe	−0.2630***	−0.2637***	H3a
	(0.0025)	(0.0025)	H3b
F	20750.67	19966.23	
P	0.0000	0.0000	
R^2	0.9721	0.9721	
Root MSE	0.5235	0.5233	

$p < 0.001$*** $p < 0.005$** $p < 0.01$*

Table 2 presents the results of our fixed-effects analysis of the basic model (Model A) and of the extended model (Model B). The *P* of these two models are significant at 0.001 level, that is, these two models are both effective. The R^2 of these two models reaches 0.9721, which means that there are basically no omitted variables in the models. Both *Root MSE* are nearly 0.52 that is a smaller one. The smaller the value of *Root MSE* is, the better the regression effect will be. To sum up, brand effect is related to customer repurchase behavior after unsatisfied experience, which can confirm H4 through these two models.

Model A shows the basic model, covering several explanatory variables affecting customer repurchase behavior after unsatisfied experience. The findings of this model on the repurchase behavior variables are generally consistent with those of prior studies. We also find that transaction-specific satisfaction has a negative influence on customer repurchase behavior after unsatisfied experience, and that purchase experience can influence repurchase behavior after unsatisfied experience.

In model A, purchase experience is a significant predictor of customer repurchase behavior after unsatisfied experience. Its coefficient is −0.2630 ($P < 0.001$), negatively influencing the dependent variable. Meanwhile, overall satisfaction coefficient is 0.1418 ($P < 0.001$), positively affecting repurchase behavior after unsatisfied experience. And transaction-specific satisfaction negatively influences customer repurchase behavior after unsatisfied experience, and its coefficient is −0.0461 ($P < 0.001$). The opposite effects of these two factors reflect that different kind of satisfaction has different influence on repurchase behavior after unsatisfied experience. That is, customer repurchase behavior is indeed influenced by unsatisfied experience. Besides, overall satisfaction variance positively affects repurchase behavior after unsatisfied experience. Though the coefficient (0.0499) is small, its *P* is significant ($P < 0.001$).

Model B is developed based on Model A, which also reveals that brand has an influence on customer repurchase behavior after unsatisfied experience. It contains the same independent variables as Model A, and additionally includes another control factor, satisfaction after unsatisfied experience variance, which is related to different states of satisfaction. Repurchase behavior after unsatisfied experience is strongly influenced by purchase experience ($C. = -0.2637$, $P < 0.001$), followed by overall satisfaction ($C. = 0.1396$, $P < 0.001$), transaction-specific satisfaction ($C. = -0.0438$, $P < 0.001$), overall satisfaction variance ($C. = 0.0438$, $P < 0.001$) and satisfaction after unsatisfied experience variance ($C. = 0.0216$, $P < 0.001$), which can prove the accuracy and validity of Model A as well. Comparatively, satisfaction after unsatisfied experience variance has the least impact on repurchase behavior after unsatisfied experience.

In addition, the coefficients of control variables show that total purchase behavior and frequency of unsatisfied experience indeed positively affect customer repurchase behavior after unsatisfied experience. When customers suffer unsatisfied experiences, especially for the first time, their unsatisfied emotion has a strong effect on customers' intent and behavior. That is, unsatisfied emotion will change customers' attitude towards products next time when they shop.

Table 3. Model a brand effects significance

Brand (top 1–20)	Total sales	LSDV coefficient	Standard error	P
L'Oreal Paris	26269	−0.1977	0.0267	0.000
Conair	22258	−0.0853	0.0319	0.007
OPI	19604	−0.1801	0.0248	0.000
Olay	18320	−0.1232	0.0247	0.000
Revlon	17648	−0.0949	0.0256	0.000
Neutrogena	16852	−0.0798	0.0237	0.001
Maybelline	15421	−0.0658	0.0221	0.003
NYX	10641	−0.0507	0.0228	0.026
SHANY Cosmetics	10511	−0.0579	0.0264	0.028
Remington	8677	−0.0770	0.0272	0.005
HSI PROFESSIONAL	8651	−0.0629	0.0407	0.122
BaBylissPRO	7950	−0.0631	0.0329	0.048
Bare Escentuals	7924	−0.0578	0.0290	0.055
COVERGIRL	7814	−0.0464	0.0235	0.046
WEN® by Chaz Dean	7683	−0.0540	0.0277	0.049
Dove	7319	−0.0801	0.0244	0.051
Essie	7199	−0.0529	0.0260	0.001
Paul Mitchell	6866	−0.0582	0.0329	0.041
e.l.f. Cosmetics	6798	−0.0054	0.0224	0.810
Garnier[a]	6717			

[a]The last brand Garnier is adopted as the base brand.

As can be seen from Table 3, most of the brand dummy variables are significant ($P < 0.05$), so we can reject the null hypothesis that all brand dummy variables are 0. It indicates that brand has an effect on customer repurchase behavior after unsatisfied experience, and that mixed regression should not be used in this model.

Furthermore, the brand effect coefficients are all negative, which means the sales volume of a brand is inversely proportional to the frequency of repurchase behavior after unsatisfied experience. The table shows that brands with large sales volume have a more negative influence on repurchase behavior after unsatisfied experience than those with small sales, because the former's absolute value of the coefficients are larger. We find that after unsatisfied experience, the frequency of repurchase behavior on popular brand is less than that on unpopular brand. That is, customers prefer to repurchase unpopular brand after unsatisfied experience.

4.2 Robust Test

To test our model and to test whether the brand effect exists, we conduct Robust test on the research results.

First, we choose part of sample data to construct a fixed-effects model. The reason to do this is that if the fixed effect does exist, it should be independent of data. That is, whether a model is effective or not doesn't depend on its amount of data. Then, we use these data to construct a random-effects model.

There are 9972 reviews in this sample, and we first carry out the Hausman test. The results are presented as follows:

Table 4. Hausman test results

	Fixed-effects	Random-effects	Difference	S.E.
Constant	−1.4321	−1.4524	0.0203	0.0042
Control variable				
ftpb	0.8099	0.8117	−0.0018	0.0003
fue	0.2589	0.2617	−0.0028	0.0006
osv	0.0414	0.0486	−0.0072	0.0009
suev	0.0259	0.0106	0.0153	0.0019
Explanatory variable				
tss	−0.0570	−0.0595	0.0025	0.0006
pe	−0.2553	−0.2603	0.0050	0.0006
osat	0.1661	0.1713	−0.0052	0.0010
chi(2)	85.11			
P	0.0000			

From Table 4, since the P is 0.000, the result is strongly significant, so a fixed-effect model, rather than a random-effects model, should be used.

From Tables 3 and 4, we can see that most of dummy variables are significant, but the rest are not. So we use joint significance test and examine the joint significance of all the dummy variables. The result F is 6.99, and P is 0.000, which confirms that brand effects should be included in the model.

Additionally, considering that time may have an impact on the model, to avoid omitting variable bias, we also use the total data to construct a time fixed-effects model,

Table 5. Time fixed-effects significance

Time	P
2014	0.251
2013	0.262
2012	0.250
2011	0.257
2010	0.241
2009	0.309
2008	0.287
2007	0.303
2006	0.395
2005	0.508
2004	0.721

*2003 is adopted as the base period.

considering that time may have an impact on the model. But from Table 5, the results show that all time dummy variables are not significant because all P values are large. So we can conclude that there is no time effect.

4.3 Text Mining

To find out what factors influence customers to repurchase a brand after unsatisfied experience, we use text mining to find out the key which customers truly care about. Based on beauty industry reviews, we use term-frequency analysis through Python 3.0. There are 134,531 words given by customers in online reviews.

We exclude several words like "the", "was", "in" and so on.

Table 6. High-frequency words (top 1–40)

Words 1–10	Times	Words 11–20	Times	Words 21–30	Times	Words 31–40	Times
Hair	416142	Price	75023	Shampoo	53070	Conditioner	37173
Product	397379	Works	71050	Smells	47929	Quality	36520
Like	302478	Bottle	67839	Cream	45213	Soft	36165
Skin	191057	Look	66484	Light	44549	Thick	35996
Color	106645	Try	63487	Oil	44129	Disappointed	35832
Smell	97360	See	60517	Amazon	41194	Hard	35216
Love	83817	Feel	60438	Small	41094	Natural	34538
Face	82648	Brush	58055	Lotion	40870	Worth	33744
Dry	77600	Scent	56168	Purchased	38973	Old	33512
Products	75802	Money	54449	Reviews	38643	Wash	32432

From Table 6, these words are related to the reasons why customers repurchase a brand after unsatisfied experience. Most customers may lay more emphases on whether products are useful to their hair, skin or face, whether the color of products looks well, whether the price is suitable and whether exterior design matches product. These factors are more related to product itself when customers repurchase the same brand after they suffer unsatisfied experiences. To sum up, we find that product quality, product efficacy, product packaging, price, reviews and purchase experience can influence customers' repurchase behavior after unsatisfied experience.

In addition, the word "like" is used about 302,478 times and the word "love" is used 83,817 times, which means in bad reviews, customers do not always complain about products with negative words, but positive words will also be given. These words are useful to managers and for firms.

5 Conclusion

The paper proposes and tests fixed-effects models through LSDV method to examine the factors influencing customer repurchase behavior after unsatisfied experience. In doing so, it provides a theoretical and empirical improvement for prior studies on repurchase behavior. It additionally provides another new factor due to its particularity; for instant, influence factor transaction-specific satisfaction will appear after unsatisfied experience.

Most importantly, this study finds that the brand has an important impact on the repurchase behavior after unsatisfied experience, and that there exists brand effect in repurchase behavior after unsatisfied experience. Through the LSDV method, the sales volume of the brand is related to the repurchase behavior after unsatisfied experience. The higher the brand sales volume is, the less frequent repurchase behavior after unsatisfied experience will be. This may be related to the brand attributes [34].

In addition, from the perspective of control variables, the coefficients of them are relatively large. The reason is possible that the total number of purchase can reflect the purchase power of consumers, the customers' income. Because Seiders and Voss [35] find that income and repurchase behavior are positively correlated.

Finally, this study finds the factors influencing customers repurchase behavior of the same brand after unsatisfied experience are more related to product itself, but less to channel.

6 Limitations and Future Directions

According to the models, it is clear that brand has a strong influence on repurchase behavior after unsatisfied experience. However, due to data limitations, we only suggest a small number of factors about how brand affects customer repurchase behavior after unsatisfied experience. It is necessary to conduct an in-depth study on how brand affects customer repurchase behavior after unsatisfied experience, namely, what its internal mechanism is and how it works.

This study does not systematically study the internal psychological mechanism affecting consumer repurchase behavior. According to the previous research, different generations of customers react differently to the same thing [3]. After the service failure, customers' complaints and repurchase behaviors are also different.

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