

# Analyzing the Impact of Live Chat Service Implementation on Customer Online Shopping Satisfaction

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## Abstract

*A live chat service is a tool embedded in an online shopping website that allows online vendors to instantly communicate with consumers. Empirical quantification of how live chat affects customer satisfaction in an online shopping scenario facilitates the calculation of the return of investment of the implementation of the live chat service. To this end, this paper obtained 84405 pieces of purchase-and-comment data during 2010-2012 from a major online shopping websites in China, which implemented its live chat service in January, 2012. Results suggest that implementing live chat service can indeed improve customer satisfaction. Meanwhile, such effect is more pronounced for third-party brands, experience goods purchases, high perceived risk products, and cross-buying. This study contributes by pioneeringly conducting before-and-after comparison based on real implementation data, as well as offering critical suggestions to online shopping website managers regarding the decision and optimization of live chat service implementation.*

**Keywords:** *live chat, implementation, before-and-after, customer satisfaction, online shopping, e-commerce*

## I. Introduction

When customers walk into a brick-and-mortar store, they are highly likely to be warmly greeted by one or more salespersons. Such might not be the case if these customers visit an online shopping website, except for those websites that offer live chat service. A live chat service is a tool embedded in an online shopping website that allows online vendors to instantly communicate with consumers [1]. For example, wine.com, an online wine retailer, offers its live chat service every day during 5am–8pm local time. A customer can easily start a conversation with a wine expert during these "chatting hours".

Live chat service has been reported to improve customer satisfaction. Wells Fargo, a financial services company, attributed its high customer satisfaction scores to the adoption of online chat in 2008 [2]. Likewise, after AT&T, a wireless carrier, introduced a chat function to its customer care service in 2013, its customer satisfaction increased to a historical high level [3]. Despite such industry reports and anecdotes, there has not been an empirical study that quantifies how live chat affects customer satisfaction, needless to say in an online shopping scenario. Such quantification is important, because it facilitates the calculation of the return of investment of the implementation of the live chat service, which bears both software and labor costs.

Existing studies of live chat service implementation have another limitation of not differentiating the studied purchases [4], or merely focusing on a single type of product [1] or customer [5]. In other words, existing studies have not explored the moderating effect of product or customer. However, these moderating effects are much worth studying. For example, if the positive impact of live chat service implementation on customer satisfaction is stronger for house brands (e.g. Amazon.com's own products) than for third-party brands (e.g. small companies' products listing on Amazon.com) it is reasonable for the shopping website to allocate more resource to the house brands, given the same amount of total resource. To initiate such optimization, one needs to characterize the moderating effects.

Based on these research gaps, the goal of this study is to quantify the impact of live chat service implementation on customer online shopping satisfaction, which is further moderated by product and customer. The rest of this paper is structured as follows. The related work section reviews extant studies about live chat service implementation and customer online shopping satisfaction. The theoretical framework section develops the hypotheses, including one main effect and four moderating effects, followed by the data and method section describing the dataset, variables, and model. The results section reports the empirical evidences, with the discussion section offering explanations and implications. The conclusion section highlights the key findings and addresses limitations.

The theoretical contribution of this paper is embedded in a complete theoretical framework of live chat service implementation on customer online shopping satisfaction, incorporating product and customer moderators. Because of the scarcity of live chat service implementation data, previous studies have limited to customers' adoption of live chat service after website implementation. To the authors' knowledge, this study is the first to conduct before-and-after comparison based on real data, which is a meaningful complement to existing literature.

The managerial contribution of this paper manifests as critical suggestions to the decision and optimization of live chat service implementation. By quantifying the benefit of live chat service implementation in terms of enhanced customer satisfaction, online shopping website managers can better evaluate the return of investment in such service. Moreover, this study has also detected the slight difference in the strength of benefit between different products and between different customers. In this way, online shopping website managers can further optimise their resource allocation among products and customers to achieve the maximum overall satisfaction as well as corporate profit and value.

## II. Related Work

### 2.1 Live Chat Service Implementation

Online shopping, though being spatially and temporally convenient for customers, is not without drawback. When shopping online, a customer faces the challenge of isolation from the product or the salesperson, which leads to uncertainty of product property or quality, or even poor shopping experience such as refund or dispute [6]. To help customers counter these challenges, some online shopping websites have implemented live chat services that resemble the physical store shopping experience [7] and through which customers express needs instantly. Moreover, Kang et al. [4] found that customers believe live chat helps reduce information asymmetry and guard against seller opportunism.

A few studies have confirmed the benefits of live chat service implementation. Ou and Davison [8] associated TaoBao's success over eBay, both e-commerce platforms, in China with TaoBao's adoption of its live chat system. Moreover, Ou and Pavlou [5] discovered that a buyer quickly establishes interpersonal relationship with a seller during a live chat, featuring understanding, reciprocity, and harmony, all contributing to purchase and repurchase intentions. Nevertheless, the study of the impact of live chat service implementation on customer online shopping satisfaction has been missing from existing literature.

Regarding the methodology of live chat service implementation studies, the research tools have gradually shifted from small-dataset interview [8] and questionnaire [5] to large-scale granular data analyses [1] so as to capture the dynamics in real situations. The latest effort features Tan et al. [1] who obtained live chat session data from the server of an e-commerce website and constructed a variable telling if a conversation was initiated between a seller and a customer. A similarity among these data-rich studies is that all the data were collected after the implementation of the live chat services. Therefore, these studies focused on different customers' adoption or no adoption of live chat. Inevitably, some customers may prefer live chat while others may shop by themselves; this preference could lead to bias. Alternatively, one can directly investigate the impact of live chat service implementation by comparing the same group of customers' online shopping satisfaction before and after the implementation, in which way the preference cancels itself and introduces no bias. This type of study has not yet

been reported, which may result from data scarcity.

## 2.2 Customer Online Shopping Satisfaction

Cognitively, customer satisfaction is the degree of consistency between the real outcomes of buying and using a product, and the expectation during or before the purchase [9]. A more emotional definition was later constructed by Westbrook and Reilly [10] that customer satisfaction refers to the delightful emotional condition triggered by the evaluation of a product or a service. These definitions apply to both offline and online scenarios [11,12].

To measure customer online shopping satisfaction, researchers can either resort to scale-based questionnaires such as The American Customer Satisfaction Index [13] or simply use online ratings posted by customers on e-commerce websites [14]. Whichever the measuring technique, customer satisfaction has been proved to increase post-purchase intention, reinforce loyalty, boost sales, multiply revenue, strengthen profit, and enhance firm market value.

As for the antecedents of customer online shopping satisfaction, research has shown that the success factors include website quality, product attributes, product quality, quality of customer service, perceived value, fulfilled expectation, reduction of expectation disconfirmation. Meanwhile, existing studies have observed that the efforts made to increase customer satisfaction generate different impact on different product types or different customer segments.

## III. Theoretical Framework

The theoretical framework of this study incorporates one main effect and four moderating effects.

### 3.1 Main Effect

Online shopping has the disadvantage of isolating customers from products and salespersons, potentially resulting in uncertainty of product attributes or quality [15]. Customers may also form inaccurate expectation towards the products [16]. These all increase the risk of poor shopping experience such as lack of help, wrong product or function, or even dispute, which could greatly compromise customer satisfaction [17]. The implementation of live chat service enables the communication between buyers and sellers before the purchases. Not only can they exchange information such that information asymmetry and the resulting product mismatch are greatly lessened [4], but the sellers can offer additional advices regarding buyers' expectation disconfirmation to further guarantee final satisfaction [18]. Therefore, the first hypothesis and main effect of this study is proposed as follows.

H1: Live chat service implementation increases customer online shopping satisfaction.

### 3.2 Moderating Effects

#### 3.2.1 Brand Familiarity

For a product distributor, its products can be divided into two types of brands based on the involvement of the manufacturing of the products. According to Anderson and Robertson [19], if a distributor directly receives products from an upstream company and then sells the products, these products are categorised as third-party brands (or principals' brands). In this case, the distributor is not involved in the manufacturing of the products. On the contrary, if a distributor has its own brands, and manufactures the products or has them manufactured to its own specifications, the products are categorised as house brands (or proprietary brands). Some major product distributors, including both brick-and-mortar and online, sell house brands side-by-side with their third-party brands. Although big companies, even for those who do have their individual direct online marketing channels, may also sell their products via online distributors [20], the principals of online distributors are mostly small companies that cannot build their own channels due to economic concerns.

A major difference of these third-party brands from house brands is brand familiarity. Brand familiarity refers to the quantity and quality of a customer's association with a brand [21], or the level of a consumer's experience and information about a brand [22]. In this sense, consumers are less familiar with third-party brands because of limited awareness, but more familiar with house brands because of strong experience and association. Familiar brands are associated with trustworthiness and high quality, especially in an online shopping scenario when the direct examination of a product is not feasible [23]. Less familiar brands, however, do not fully enjoy these privileges such that their customers are facing greater uncertainty of product attributes and quality. Consequently, once live chat service is implemented, it can significantly ease these customers' anxiety of uncertainty and lack of trust [6]. In comparison, brands of high familiarity evoke less uncertainty, which reduces the likelihood of poor shopping experience. For this reason, the implementation of live chat service is expected to have smaller impact on these customers' satisfaction. Based on the above deduction, the following hypothesis and moderating effect is proposed.

H2: The impact of live chat service implementation on customer online shopping satisfaction is more pronounced for less familiar brands than for more familiar brands.

### 3.2.2 Product Category

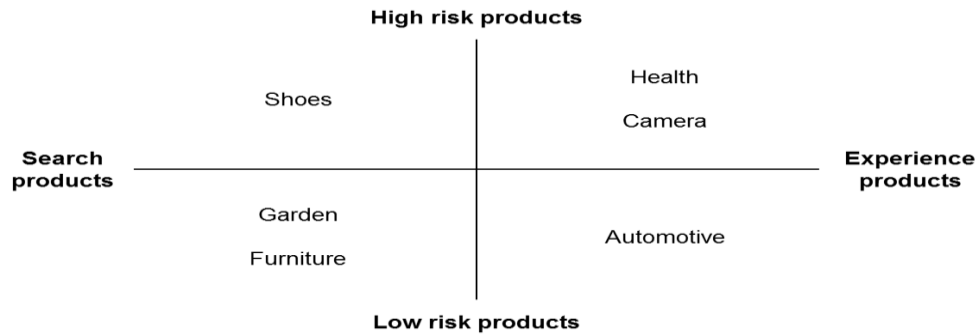
Products are classified into search and experience goods per customers' capability of acquiring product quality information before purchase [24]. For example, shoes and home furniture are search products, whereas health and beauty are experience products. Nelson [24] argued that a customer conducts minimum pre-purchase research for experience goods, yet performing comprehensive study for search goods. Although Hoch and Ha [25] argued that, in an online shopping scenario, greater effort is involved in assessing experience features, with evidence showing experience goods requires deeper search [26], the search is very likely to be focused on other consumers' experience, e.g., the user generated contents in the form of rating and review. In this situation, live chat service can offer limited help, because the customers may not buy the story that every potter praises his own pot, especially "experience pot". Meanwhile, live chat operators are more likely to be trained on providing search attributes of products since those are objective rather than subjective product information. It is therefore reasonable to speculate that the benefit of live chat service implementation, including more accurate expectation and reduced disconfirmation, is stronger for search goods buyers, which further leads to larger increment in customer satisfaction. Hence, the corresponding moderating effect is hypothesized as follows.

H3: The impact of live chat service implementation on customer online shopping satisfaction is more pronounced for search goods purchases than for experience goods purchases.

### 3.2.3 Risk Perception

Customers perceive some products as high-risk and others as low-risk [27]. For products with high perceived risk, such as electronics and musical instruments, customers suffer great uncertainty [28]. It is noted here that high- or low-risk does not necessarily correlate with search or experience goods [26,28]; see Figure 1 for some examples. Because of the uncertainty nature of high perceived risk products, they are associated with greater probability of negative consequences. As a result, customers are more conservative and concerned when purchasing high perceived risk products [29]. The implementation of live chat service provides a communication tool for sellers to establish trust with buyers, especially for high perceived risk products buyers, and help them make better decisions [30]. Therefore, it makes good sense to hypothesize the following moderating effect.

H4: The impact of live chat service implementation on customer online shopping satisfaction is more pronounced for high perceived risk products than for low perceived risk products.



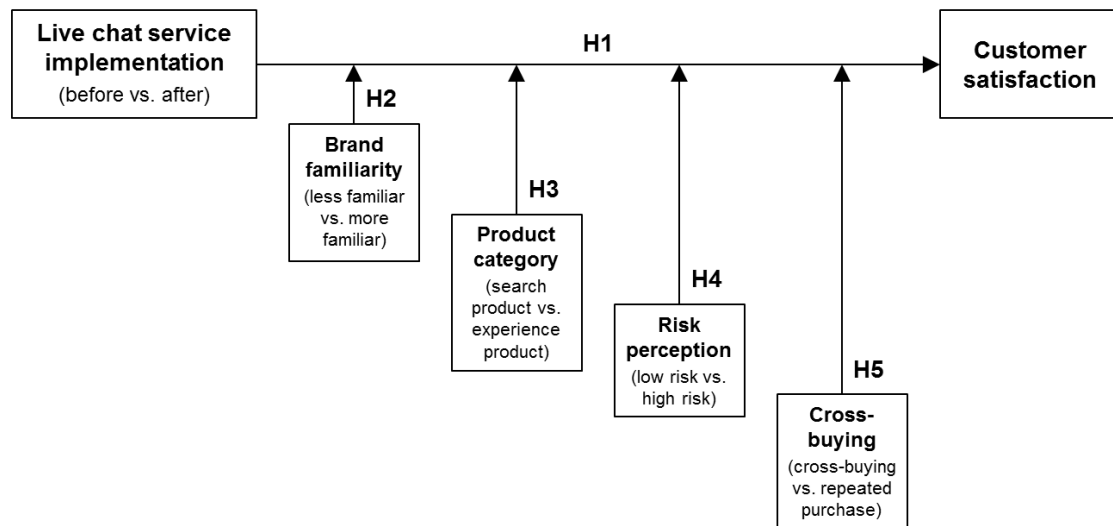
*Figure 1 Examples of search/experience and low/high risk products*

### 3.2.4 Cross-buying

Customers conduct cross-buying on online shopping websites. Cross-buying is defined as customers' buying extra kinds of goods from the current provider beyond the kinds they already have bought [31]. In contrast, if customers buy products that they have once bought, the purchase is defined as repeated purchase. Because cross-buying customers are purchasing new products, they are experiencing larger uncertainty than repeat-purchase customers. The implementation of live chat service can greatly ease the anxiety arising from the perceived uncertainty. In addition, the convenience triggered by such one-stop-shopping mode [32] can further strengthen the benefit of live chat service on customer satisfaction. Therefore, the final hypothesis and moderating effect of this study is proposed as follows.

H5: The impact of live chat service implementation on customer online shopping satisfaction is more pronounced for cross-buying than repeated purchase.

In summary, the theoretical framework of this study is shown in Figure 2.



*Figure 2 Theoretical framework*

## IV. Data and Method

The data of this study was obtained from one of the top three online shopping websites in China, which was founded in the early 2000s. Because the website implemented its live chat service in January, 2012, from its over 300 million active users, 50000 of them were randomly selected to be further screened, all of whom had created their accounts before June, 2010, at least one and a half years before the implementation. Afterwards, a screening

process was conducted to rule out the users who had zero purchase record during the period between July, 2010 and June, 2012. From the remaining 10079 users, their 262296 purchase records and 84405 pieces of purchase-and-comment data during that period were retrieved and examined to test the hypotheses. Here, a purchase-and-comment is defined as that a user makes a purchase on the website, and then leaves a comment about the purchase. See Table 1 for a de-tailed description of the data and the variables.

**Table 1 Data and variables**

Purchase-and-comment data	Information in data	Variable in hypotheses	Variable name	Variable value
1. Rating of the purchase	The rating assigned by the customer, ranging from one to five	Customer satisfaction	<i>Rate</i>	1, 2, 3, 4, 5
2. Date of a purchase	The date when a purchase was made by a customer	Live chat service implementation	<i>After</i>	0, if the purchase happened in July, August, September, October, November, or December 1, otherwise
			<i>Treat</i>	0, if the purchase happened before July 2011 1, otherwise
3. Brand type	Third-party brand, or house brands	Brand familiarity	<i>Brand</i>	0, more familiar brand (house brand) 1, less familiar brand (third-party brand)
4. Product name	The name of the product	Product category	<i>Search</i>	0, experience product* 1, search product
		Risk perception	<i>Risk</i>	0, low risk* 1, high risk
5. Purchase history	The name(s) of the product(s) purchased by the customer before this purchase	Cross-buying	<i>Cross</i>	0, repeated purchase 1, cross-buying Note 1: Data before July 2010 was also obtained to define Cross particularly for the first purchase during the period from July 2010 to June 2012. Note 2: If a purchase is the first purchase of a user throughout history, the purchase is defined as cross-buying.
6. Average rating	The average rating assigned by the customer regarding the product(s) purchased in the last 12 months	Control	<i>AvRate</i>	An interval scale between 1 and 5
7. Purchase frequency	The number of purchase(s) made by the customer in the last 12 months	Control	<i>PurFreq</i>	A natural number
8. Comment frequency	The number of comment(s) posted by the customer in the last 12 months	Control	<i>ComFreq</i>	A natural number
9. Length of relationship	The number of days between this purchase and the very first purchase of the customer	Control	<i>ReLeng</i>	A natural number

Purchase-and-comment data	Information in data	Variable in hypotheses	Variable name	Variable value
10. Sequence of comment	The sequence of the comment among all the comments of the product	Control	<i>ComSeq</i>	A positive whole number
11. Product price	The price of the product	Control	<i>Price</i>	Denominated in RMB

\*Based on Nelson [24], and Huang et al. [26], experience goods include foods, wine, cosmetics, mother and babies, health and medicine, books, watch and jewelry, automotive parts and accessories. In the meantime, search goods include kitchens, house furnishings and furniture, pet items, office suppliers, sports equipment, cellphone, computer, cameras, garden and suppliers.

Based on Kushwaha and Shankar [28], the following products have been classified into the high-risk category: computer, cell-phone, camera, sports equipment, foods, wine, cosmetics, mother and babies, pet items, health and medicine, watch and jewelry. Meanwhile, low risk products include automotive parts and accessories, books, kitchens, house furnishings and furniture, garden and suppliers.

To quantitatively test H1 (i.e. the main effect), the variables were organized into the following difference-in-differences (DID) regression model [33,34].

$$Rate_{ijt} = \beta_0 + \beta_1 * After_t * Treat_{it} + \beta_2 * After_t + \beta_3 * Treat_{it} + \beta_4 * Brand_{jt} + \beta_5 * Search_{jt} + \beta_6 * Risk_{jt} + \beta_7 * Cross_{jt} + \alpha_i + \beta_8 * AvRate_{it} + \beta_9 * Ln(PurFreq_{it}) + \beta_{10} * ComFreq_{it} + \beta_{11} * ReLeng_{it} + \beta_{12} * ComSeq_{ijt} + \beta_{13} * Ln(Price_j) + A_t + \varepsilon_{ijt} \quad (1)$$

In Eq(1), the dependent variable  $Rate_{ijt}$  reflects customer satisfaction measured by the rating assigned by customer  $i$  for product  $j$  at time  $t$ . One dummy variable  $After_t$  denotes the elapse of months, with live chat implementation starting to take effect on the first half a year ( $After_t = 1$ ). The other dummy variable  $Treat_{it}$  stands for the elapse of years, with live chat implementation starting to take effect on the second sample year ( $Treat_{it} = 1$ ). With  $\beta_2$  capturing the effect of pass of month and  $\beta_3$  capturing the effect of pass of year, it leaves  $\beta_1$ , the coefficient of the cross term  $After_t * Treat_{it}$ , to characterize the pure effect of live chat implementation.

Eq(1) also contains four types of control variables. Firstly, there is the term  $\alpha_i$  that portrays the individual fixed effects on rating to absorb time-invariant factors. Such effects include gender, education background, et al. Secondly, there are terms that depict factors which vary among individuals and across time. One of these terms is  $AvRate_{it}$ , the average rating assigned by the customer regarding the product(s) purchased in the last twelve months. The rationale behind is that picky customers, measured by their previous ratings, are more likely to assign lower ratings in the future. The other terms, namely  $PurFreq_{it}$ ,  $ComFreq_{it}$ ,  $ReLeng_{it}$ , and  $ComSeq_{ijt}$ , quantify the online shopping knowhow of a customer. With more shopping experience (e.g.  $PurFreq$ ) or more reference from other customers (e.g.  $ComSeq$ ), a customer may presumably conduct a more satisfying purchase and thus provide a higher rating. Thirdly, the price of the product is controlled, because it is believed that customers have higher expectation for more expensive products, which may lead to larger likelihood of lower rating. Finally, to control the time varying trend,  $A_t$  is introduced as a vector of time related dummy variables, including month, week, and day.

## V. Results

### 5.1 Descriptive Statistics

The descriptive statistics of this study are summarised in Table 2. From the total 84405 observations, the customers gave an average rating of 4.637. The majority of the purchased goods were house brands (high familiarity, around 86%). Regarding product type, around 23% of the purchased goods are experience goods; high risk goods took up

around 65% of all goods. As for purchase history, cross-buying is not so common (less than 15%). The descriptive statistics of the control variables are also reported.

**Table 2 Descriptive statistics**

Variable	Mean	Std. Dev.	Min	Max
DV				
<i>Rate</i>	4.656	0.674	1	5
IV				
<i>Treat</i>	0.489	0.492	0	1
<i>Brand</i>	0.136	0.342	0	1
<i>Search</i>	0.234	0.423	0	1
<i>Risk</i>	0.649	0.477	0	1
<i>Cross</i>	0.147	0.354	0	1
Control				
<i>AvRate</i>	4.438	1.177	1	5
<i>Ln(PurFreq)</i>	3.387	1.269	0	7.927
<i>ComFreq</i>	5.132	2.245	0	76
<i>ReLeng</i>	0.027	0.473	0	25
<i>ComSeq</i>	218	679	1	11004
<i>Ln(Price)</i>	4.499	1.468	0.693	11.92
N	84405			

The correlation matrix of the above data is reported in Table 3 and provides two preliminary clues. On one hand, the positive correlation of *Rate* with *Treat* (0.060,  $p < 0.05$ ) is in line with H1 (i.e. the main effect), though it still requires DID validation to rule out the influence of time. The positive correlation also agrees with Figure 3, which demonstrates a sharp rising edge of average rating around the month of live chat service implementation. On the other hand, the relatively weak correlation of *Search* and *Risk* (0.024,  $p < 0.05$ ) has justified treating them as different moderators.

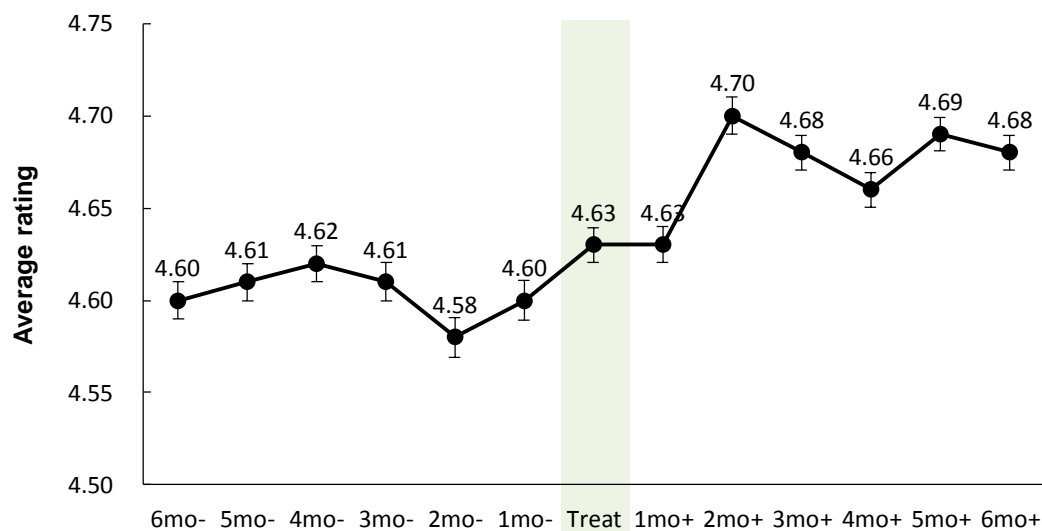
**Table 3 Correlation matrix**

Variables	1	2	3	4	5	6	7	8	9	10	11
1. <i>Rate</i>											
2. <i>Treat</i>	0.060*										
3. <i>Brand</i>	-0.041*	0.169*									
4. <i>Search</i>	-0.027*	-0.025*	0.288*								
5. <i>Risk</i>	-0.040*	-0.266*	-0.023*	0.024*							



Variables	1	2	3	4	5	6	7	8	9	10	11
6. <i>Cross</i>	0.007 *	0.007 *	0.116* *	- 0.447 *	0.043 *						
7. <i>AvRate</i>	0.047 *	0.033 *	- 0.018 *	- 0.035 *	- 0.030 *	- 0.085 *					
8. <i>Ln(PurFreq)</i>	0.074 *	0.543 *	0.121 *	- 0.036 *	- 0.446 *	- 0.040 *	0.109 *				
9. <i>ComFreq</i>	0.058 *	0.207 *	0.023 *	- 0.056 *	- 0.174 *	- 0.079 *	0.122 *	0.636 *			
10. <i>ReLeng</i>	0.012 *	0.014 *	- 0.018 *	- 0.008 *	- 0.023 *	0.008 *	- 0.004 *	0.023 *	- 0.007 *		
11. <i>ComSeq</i>	0.027 *	0.192 *	0.009 *	- 0.060 *	- 0.157 *	- 0.087 *	- 0.036 *	0.566 *	0.955 *	- 0.008 *	
12. <i>Ln(Price)</i>	0.004 *	- 0.008 *	0.077 *	0.172 *	- 0.014 *	0.182 *	- 0.063 *	- 0.054 *	- 0.042 *	0.003 *	- 0.043 *

\* $p < 0.05$



**Figure 3 Average rating before and after the live chat service implementation**  
(6mo- = 6 months before implementation; Treat = the month of implementation; 6mo+ = 6 months after implementation)

## 5.2 Main Effect

Four models were applied in order to estimate the impact of live chat service implementation on customer online shopping satisfaction regarding Eq(1). The baseline DID model is reported in column (1) of Table 4. Because the coefficient of *After \* Treat* is positive and significant ( $\beta_1=0.065$ ,  $p<0.001$ ), live chat service implementation is thus

believed to have a positive influence on customer online shopping satisfaction. Moreover, the incorporation of control variables, including the control of individual fixed effect, has not changed the sign and significance level of  $\beta_1$ ; see columns (2)–(4) in Table 4. It is therefore confirmed that H1 is supported.

**Table 4 Impact of live chat service implementation on customer online shopping satisfaction**

	DV: <i>Rate</i>			
	(1)	(2)	(3)	(4)
<i>After * Treat</i>	0.065*** (0.011)	0.072*** (0.011)	0.072*** (0.010)	0.072*** (0.011)
<i>After</i>	0.043** (0.014)	0.039** (0.011)	0.024** (0.012)	0.028** (0.012)
<i>Treat</i>	0.030*** (0.008)	-0.000 (0.010)	0.016* (0.008)	0.030* (0.014)
<i>Brand</i>		-0.098*** (0.013)		-0.111*** (0.010)
<i>Search</i>		-0.007 (0.008)		-0.009 (0.007)
<i>Risk</i>		0.029*** (0.007)		0.026*** (0.006)
<i>Cross</i>		-0.038*** (0.008)		-0.022** (0.007)
<i>AvRate</i>		0.029*** (0.002)		0.003*** (0.001)
<i>Ln(PurFreq)</i>		0.034*** (0.004)		-0.003 (0.007)
<i>ComFreq</i>		-0.001 (0.002)		-0.001 (0.002)
<i>ReLeng</i>		0.008 (0.004)		0.007 (0.004)
<i>ComSeq</i>		0.001*** (0.000)		0.001*** (0.000)
<i>Ln(Price)</i>		0.000 (0.000)		0.000 (0.000)
Constant	4.548*** (0.014)	4.270*** (0.022)	4.572*** (0.012)	4.572*** (0.027)
Individual fixed effect	N	N	Y	Y
Time fixed effect	Y	Y	Y	Y
N	84405	84405	84405	84405
Adjusted R <sup>2</sup>	0.006	0.021	0.009	0.021

Standard errors in parentheses; \*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

### 5.3 Moderating Effects

After validating the main effect, this study proceeded to analyze the potential heterogeneous effect across products (H2–H4) and across customers (H5). For this purpose, four interaction terms have been added to Eq(1) to form Eq(2).

$$\begin{aligned}
 Rate_{ijt} = & \beta_0 + \beta_1 * After_t * Treat_{it} + \beta_2 * After_t + \beta_3 * Treat_{it} \\
 & + \beta_4 * Brand_{jt} + \beta_5 * Search_{jt} + \beta_6 * Risk_{jt} + \beta_7 * Cross_{jt} \\
 & + \beta_8 * After_t * Treat_{it} * Brand_{jt} + \beta_9 * After_t * Treat_{it} * Search_{jt} \\
 & + \beta_{10} * After_t * Treat_{it} * Risk_{jt} + \beta_{11} * After_t * Treat_{it} * Cross_{jt} \\
 & + \alpha_i + \beta_{12} * AvRate_{it} + \beta_{13} * Ln(PurFreq_{it}) + \beta_{14} * ComFreq_{it} \\
 & + \beta_{15} * ReLeng_{it} + \beta_{16} * ComSeq_{ijt} + \beta_{17} * Ln(Price_j) + A_t + \varepsilon_{ijt}
 \end{aligned} \tag{2}$$

Table 5 addresses the estimation results of these heterogeneous effects, with the first four models each containing only one three-way-interaction term and the last model containing all the three-way-interactions terms. According to column (1), the main effect (*After \* Treat*) holds true ( $\beta_1=0.073$ ,  $p<0.001$ ). Meanwhile, the coefficient of *After \* Treat \* Brand* is positive and significant ( $\beta_8=0.042$ ,  $p<0.05$ ), thus supporting H2 that the impact of live chat service implementation on customer online shopping satisfaction is more pronounced for less familiar brands than for more familiar brands. For similar reasons, H4 ( $\beta_{10}=0.050$ ,  $p<0.001$ ) and H5 ( $\beta_{11}=0.035$ ,  $p<0.1$ ) are supported, meaning that the impact of live chat service implementation on customer satisfaction is more pronounced for high perceived risk products than for low perceived risk products, and is more pronounced for cross-buying than repeated purchase. Interestingly for H3, because  $\beta_9=-0.021$  ( $p<0.1$ ), the impact of live chat is thus more pronounced for experience goods than for search goods.

**Table 5 Heterogeneous impact of live chat service implementation across products**

	DV: Rate				
	(1)	(2)	(3)	(4)	(5)
<i>After * Treat</i>	0.073*** (0.012)	0.102*** (0.010)	0.109*** (0.010)	0.095*** (0.010)	0.055*** (0.013)
<i>After</i>	0.036** (0.012)	0.036** (0.012)	0.036** (0.012)	0.038** (0.012)	0.038** (0.012)
<i>Treat</i>	-0.020** (0.008)	-0.020** (0.008)	-0.019** (0.008)	-0.006 (0.008)	-0.022** (0.008)
<i>Brand</i>	-0.089*** (0.012)	-0.093*** (0.013)	-0.107*** (0.009)	-0.109*** (0.010)	-0.112*** (0.015)
<i>Search</i>	-0.039*** (0.007)	-0.038*** (0.007)	-0.032*** (0.008)	-0.010 (0.007)	-0.038*** (0.008)
<i>Risk</i>	-0.014** (0.007)	0.002 (0.006)	0.002 (0.006)	0.022*** (0.006)	-0.013* (0.007)
<i>Cross</i>	-0.022** (0.008)	-0.027** (0.008)	-0.021** (0.008)	-0.017** (0.008)	-0.030*** (0.008)
<i>AvRate</i>	0.029*** (0.002)	0.028** (0.003)	0.029*** (0.002)	0.027** (0.004)	0.027** (0.004)
<i>Ln(PurFreq)</i>	0.045*** (0.003)	0.046*** (0.003)	0.046*** (0.003)	0.046*** (0.003)	0.046*** (0.003)
<i>ComFreq</i>	0.001 (0.002)	0.001 (0.002)	0.001 (0.002)	0.001 (0.002)	0.001 (0.002)
<i>ReLeng</i>	0.002 (0.002)	0.001 (0.002)	0.001 (0.002)	0.001 (0.002)	0.001 (0.002)
<i>ComSeq</i>	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
<i>Ln(Price)</i>	0.011** (0.004)	0.011** (0.004)	0.011** (0.004)	0.010** (0.004)	0.010** (0.004)
<i>After * Treat * Brand</i>	0.042** (0.019)				0.041** (0.015)
<i>After * Treat * Search</i>		-0.021* (0.012)			-0.022** (0.008)
<i>After * Treat * Risk</i>			0.050*** (0.011)		0.080*** (0.012)
<i>After * Treat * Cross</i>				0.035* (0.018)	0.048** (0.018)
<i>Constant</i>	4.406*** (0.018)	4.398*** (0.018)	4.394*** (0.018)	4.382*** (0.018)	4.407*** (0.018)
Individual fixed effect	Y	Y	Y	Y	Y
Time fixed effect	Y	Y	Y	Y	Y
N	84405	84405	84405	84405	84405
Adjusted R <sup>2</sup>	0.021	0.023	0.024	0.023	0.024

Standard errors in parentheses; \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.001$

#### 5.4 Robustness of Results and Further Analysis

##### 5.4.1 Addressing Endogeneity

Among the observed 262296 purchase records, only 84405 of them were accompanied by comment data, which might lead to self-selection bias. To correct such bias, Heckman's two-stage estimation method [35] was applied, with *Assign* being the DV of the first stage whether a customer assigned a rating (*Assign*=1) or not (*Assign*=0), and *Rating* being the DV of the second stage quantifying satisfaction as is in Eq(1). The model of the first stage is given in Eq(3), and Table 6 reports the regression result.

$$\begin{aligned} Assign_{ijt} = & \alpha_0 + \alpha_1 * Treat_{it} + \alpha_2 * Brand_{jt} + \alpha_3 * Search_{jt} + \alpha_4 * Risk_{jt} \\ & + \alpha_5 * Cross_{jt} + \alpha_6 * AvRate_{it} + \alpha_7 * Ln(PurFreq_{it}) + \alpha_8 * ComFreq_{it} \\ & + \alpha_9 * ReLeng_{it} + \alpha_{10} * ComSeq_{ijt} + \alpha_{11} * Ln(Price_j) + A_t + \varepsilon_{ijt} \end{aligned} \quad (3)$$

**Table 6 Heckman's first stage regression result**

	<i>Assign</i>	
	Estimation	Standard error
<i>Treat</i>	0.077***	(0.009)
<i>Brand</i>	0.653***	(0.009)
<i>Search</i>	0.131***	(0.008)
<i>Risk</i>	0.114***	(0.008)
<i>Cross</i>	-0.086***	(0.008)
<i>AvRate</i>	0.083***	(0.012)
<i>Ln(PurFreq)</i>	0.016***	(0.004)
<i>ComFreq</i>	0.001***	(0.000)
<i>ReLeng</i>	-0.016***	(0.017)
<i>ComSeq</i>	0.000***	(0.000)
<i>Ln(Price)</i>	0.045***	(0.002)
<i>Constant</i>	-1.518***	(0.021)
Time Fixed Effect	Y	
N	262296	
Pseudo $R^2$	0.062	

\*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.001$

Based on the regression result of the first stage, inverse Mill's ratio (IMR) was calculated per Eq(4), where  $\phi$  and  $\Phi$  denote the probability density function and cumulative distribution function of the standard normal distribution respectively. The calculated IMR was then incorporated into Eq(1) as a control variable to facilitate the second stage of Heckman's model, as is given in Eq(5).

$$\begin{aligned} \lambda_{ij} = & \phi(\alpha_0 + \alpha_1 * Treat_{it} + \alpha_2 * Brand_{jt} + \alpha_3 * Search_{jt} + \alpha_4 * Risk_{jt} \\ & + \alpha_5 * Cross_{jt} + \alpha_6 * AvRate_{it} + \alpha_7 * Ln(PurFreq_{it}) + \alpha_8 * ComFreq_{it} \\ & + \alpha_9 * ReLeng_{it} + \alpha_{10} * ComSeq_{ijt} + \alpha_{11} * Ln(Price_j) + A_t) \\ & / \Phi(\alpha_0 + \alpha_1 * Treat_{it} + \alpha_2 * Brand_{jt} + \alpha_3 * Search_{jt} + \alpha_4 * Risk_{jt} \\ & + \alpha_5 * Cross_{jt} + \alpha_6 * AvRate_{it} + \alpha_7 * Ln(PurFreq_{it}) + \alpha_8 * ComFreq_{it} \\ & + \alpha_9 * ReLeng_{it} + \alpha_{10} * ComSeq_{ijt} + \alpha_{11} * Ln(Price_j) + A_t) \end{aligned} \quad (4)$$

$$\begin{aligned} Rate_{ijt} = & \beta_0 + \beta_1 * After_t * Treat_{it} + \beta_2 * After_t + \beta_3 * Treat_{it} \\ & + \beta_4 * Brand_{jt} + \beta_5 * Search_{jt} + \beta_6 * Risk_{jt} + \beta_7 * Cross_{jt} \end{aligned} \quad (5)$$

$$\begin{aligned}
& + \beta_8 * After_i * Treat_{it} * Brand_{jt} + \beta_9 * After_i * Treat_{it} * Search_{jt} \\
& + \beta_{10} * After_i * Treat_{it} * Risk_{jt} + \beta_{11} * After_i * Treat_{it} * Cross_{jt} \\
& + \alpha_i + \beta_{12} * AvRate_{it} + \beta_{13} * Ln(PurFreq_{it}) + \beta_{14} * ComFreq_{it} \\
& + \beta_{15} * ReLeng_{it} + \beta_{16} * ComSeq_{ijt} + \beta_{17} * Ln(Price_j) + \beta_{18} * \lambda_{ij} \\
& + A_t + \varepsilon_{ijt}
\end{aligned}$$

Table 7 tells that after controlling selection bias, the main effect remains validated ( $\beta_1=0.368$ ,  $p<0.001$ ), again supporting H1. Meanwhile the moderating effects, namely H2, H4, H5, and the opposite of H3, are also supported.

**Table 7 Heckman's second stage regression result**

	DV: Rate	
	(1)	(2)
<i>After * Treat</i>	0.368*** (0.012)	0.420*** (0.016)
<i>After</i>	0.037** (0.012)	0.042** (0.012)
<i>Treat</i>	-0.057*** (0.008)	-0.064*** (0.008)
<i>Brand</i>	0.672*** (0.022)	0.727*** (0.026)
<i>Search</i>	-0.158*** (0.008)	-0.167*** (0.009)
<i>Risk</i>	-0.132*** (0.008)	-0.125*** (0.008)
<i>Cross</i>	0.074*** (0.008)	0.065*** (0.009)
<i>Ln(PurFreq)</i>	-0.030*** (0.004)	-0.034*** (0.004)
<i>ComFreq</i>	0.001 (0.002)	0.001 (0.002)
<i>ReLeng</i>	0.012** (0.005)	0.013** (0.005)
<i>ComSeq</i>	-0.004*** (0.000)	-0.004*** (0.000)
<i>AvRate</i>	0.010*** (0.001)	0.009*** (0.001)
<i>Ln(Price)</i>	-0.051*** (0.002)	-0.055*** (0.002)
$\lambda$	-1.665*** (0.046)	-1.786*** (0.049)
<i>After * Treat * Brand</i>		0.020** (0.007)
<i>After * Treat * Search</i>		-0.021* (0.012)
<i>After * Treat * Risk</i>		0.036*** (0.011)
<i>After * Treat * Cross</i>		0.054*** (0.018)
<i>Constant</i>	6.812*** (0.073)	6.986*** (0.077)
Individual fixed effect	Y	Y
Time fixed effect	Y	Y
N	84405	84405
Adjusted R <sup>2</sup>	0.028	0.029

Standard errors in parentheses; \*  $p<0.1$ , \*\*  $p<0.05$ , \*\*\*  $p<0.001$

#### 5.4.2 Further Analysis: Hierarchical Model

An additional check on the robustness of the findings was conducted with a hierarchical model. To be specific, the mixed model in Eq(2) was transformed to a hierarchical model by introducing random intercept and interaction coefficients, as is shown Eq(6).

$$\begin{aligned} Rate_{ijt} = & \beta_{0j} + \beta_{1j} * After_t * Treat_{it} + \beta_2 * After_t + \beta_3 * Treat_{it} \\ & + \beta_4 * Brand_{jt} + \beta_5 * Search_{jt} + \beta_6 * Risk_{jt} + \beta_7 * Cross_{jt} \\ & + \beta_8 * AvRate_{it} + \beta_9 * Ln(PurFreq_{it}) + \beta_{10} * ComFreq_{it} \\ & + \beta_{11} * ReLeng_{it} + \beta_{12} * ComSeq_{ijt} + \beta_{13} * Ln(Price_j) + A_t + \varepsilon_{ijt} \end{aligned} \quad (6)$$

where  $\beta_{0j}$  and  $\beta_{1j}$  are calculated per Eq(7) and Eq(8).

$$\beta_{0j} = \gamma_{00} + \gamma_{01} * Brand_{jt} + \gamma_{02} * Search_{jt} + \gamma_{03} * Risk_{jt} + \gamma_{04} * Cross_{jt} + \varepsilon_{0j} \quad (7)$$

$$\beta_{1j} = \gamma_{10} + \gamma_{11} * Brand_{jt} + \gamma_{12} * Search_{jt} + \gamma_{13} * Risk_{jt} + \gamma_{14} * Cross_{jt} + \varepsilon_{1j} \quad (8)$$

Table 8 reports the regression results of the hierarchical linear model. In the fixed effects panel, the main effect remains positive and significant ( $\gamma_{10}=0.043$ ,  $p<0.05$ ), which again supports H1. Also supported are the moderating effects (H2, H4, H5, and the opposite of H3), with  $\gamma_{11}=0.087$ ,  $p<0.001$ ;  $\gamma_{12}=-0.021$ ,  $p<0.1$ ;  $\gamma_{13}=0.034$ ,  $p<0.1$ ; and  $\gamma_{14}=0.036$ ,  $p<0.1$ . In the random variance components panel, it is estimated that neither the extraversion random slope  $\varepsilon_0$  nor the treatment effect random slope  $\varepsilon_1$  is significantly different from zero. This means that there is no evidence to suggest that these two factors vary by levels in this model.

**Table 8 Hierarchical model regression result**

	DV: Rate	
	Estimation	Standard error
<b>Fixed Effects</b>		
<i>After * Treat</i> ( $\gamma_{10}$ )	0.043**	0.013
<i>Treat</i> ( $\beta_3$ )	0.005	0.007
<i>Brand</i> ( $\gamma_{01}$ )	-0.146***	0.014
<i>Search</i> ( $\gamma_{02}$ )	-0.024***	0.008
<i>Risk</i> ( $\gamma_{03}$ )	0.019***	0.005
<i>Cross</i> ( $\gamma_{04}$ )	-0.025***	0.007
<i>AvRate</i> ( $\beta_8$ )	0.026***	0.002
<i>Ln(PurFreq)</i> ( $\beta_9$ )	0.032***	0.003
<i>ComFreq</i> ( $\beta_{10}$ )	-0.002	0.002
<i>ReLeng</i> ( $\beta_{11}$ )	0.003	0.005
<i>ComSeq</i> ( $\beta_{12}$ )	-0.005	-0.001
<i>Ln(Price)</i> ( $\beta_{13}$ )	0.007*	0.004
<i>After * Treat * Brand</i> ( $\gamma_{11}$ )	0.087***	0.017
<i>After * Treat * Search</i> ( $\gamma_{12}$ )	-0.021*	0.011
<i>After * Treat * Risk</i> ( $\gamma_{13}$ )	0.034*	0.016
<i>After * Treat * Cross</i> ( $\gamma_{14}$ )	0.036*	0.017
<i>Intercept</i> ( $\gamma_{00}$ )	4.350***	0.056
<b>Variance Components</b>		
<i>Residual</i> ( $\varepsilon$ )	0.446	0.668
<i>Intercept</i> ( $\varepsilon_0$ )	0.026	0.016
<i>ATE</i> ( $\varepsilon_1$ )	0.002	0.042
N	84405	

	DV: <i>Rate</i>	
	Estimation	Standard error
LL		-85868.67

<sup>\*</sup> $p < 0.1$ , <sup>\*\*</sup> $p < 0.05$ , <sup>\*\*\*</sup> $p < 0.001$

## VI. Discussion

The result that live chat service implementation increases customer online shopping satisfaction justifies online shopping websites' adoption of the service. Live chat service helps overcome online shopping's disadvantage of isolating customers from products and salespersons, and enables the communication between buyers and sellers before the purchases, facilitating information exchange and lessening expectation disconfirmation and product mismatch. It is further expected that the benefit from more satisfied customers can partially or totally offset the cost of live chat service software and labor.

Whereas the majority of the purchased goods were house brands (high familiarity), which could possibly result from the brand portfolio strategy of the studied shopping website, the impact of live chat service implementation on customer satisfaction is more pronounced for third-party (low familiarity) brands. Live chat service builds up the trust between customers and less familiar brands and reduces customers' uncertainty of product attributes and quality. For online shopping websites that already have large percentage of third-party sellers, or those that are considering arranging so, there positive return of live chat service implementation will be even greater.

The findings of this study also suggests that given the same amount of total live chat implementation resource, online shopping websites may prioritize to first cater to potential customers of high perceived risk products, as well as customers considering cross-buying, because these customers are faced with higher level of uncertainty; the implementation of live chat service helps them make better decisions. For online shopping websites that got the permission of tracking the real-time browsing history of customers, such prioritizing is feasible.

Surprisingly, the impact of live chat service implementation on customer satisfaction is more pronounced for experience goods purchases than for search goods purchases. Originally, it was expected that search goods buyers, who search products' objective specifications instead of subjective experience, can face information overload due to the rich and substantial information displayed on the screen superimposed by plentiful substitutes. Under such circumstance, live chat service may provide greater assistance to relieve the mind burden. Meanwhile, experience goods buyers have the alternative solution of reading user generated contents that appear to be more informative and trustworthy. However, the finding shows that it is the experience goods buyers who benefit more from live chat. It is therefore suggested that experience goods online shopping features greater uncertainty, and that hearing a potter praising his own pot can indeed help the shopper make better decisions.

## VII. Conclusion

This study quantifies the impact of live chat service implementation on customer online shopping satisfaction, with the moderating effects of product and customer considered. Results suggest that implementing live chat service can surely improve customer satisfaction. Meanwhile, such effect is more pronounced for third-party brands, experience goods purchases, high perceived risk products, and cross-buying than for house brands, search goods purchases, low perceived risk products, and repeated purchase.

This study is not without limitations. Firstly, the data was collected almost ten years ago. The live chat service technology, as well as its dynamics with consumers, can be constantly changing over time. Secondly, the theoretical framework can be more solid by incorporating some mediators, because many things could happen between the "good bye" of a live chat conversation and the click of "submit" button of a customer rating. Therefore, future studies are suggested to further explore the temporal validity of the findings of this study, as well as a more deep-going mechanism.

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