Omni-Channel Retailing and Firm Performance from a Customer Lifetime Value Perspective

Liu Xiangdong, Mi Zhuang*, He Mingqin
Business School, Renmin University of China, Beijing

Abstract: *In the digital era, retailers are keen to find out whether omni-channel retailing helps improve long-term firm performance. In this paper, we employ machine learning techniques on a large consumption data set in order to measure customer lifetime value (CLV) as the basis for determining long-term firm performance, and we provide an empirical analysis of the relationship between omni-channel retailing and CLV. The results suggest that omni-channel retailing may effectively enhance CLV. Further analysis reveals that this process is influenced by heterogeneous consumer requirements and that significant differences exist in the extent to which the omni-channel transition may influence CLV depending on consumer preferences for diversity of commodities, sensitivity to the cost of contract performance, and sensitivity to warehousing costs. Hence, retailers should provide consumers with a complete portfolio of goods and services based on target consumers' heterogeneous requirements in order to increase omni-channel efficiency.*

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1. Introduction

Digital technology has hastened the transition to an omni-channel retail business model (Rigby, 2011), and omni-channel retailing has gained currency among academics and the retail business community alike. However, due to high upfront costs and a lack of operational experience, this omni-channel transition has yet to result in major profitability gains for retailers. The retail business community is thus eager to learn whether an omni-channel transition will provide long-term value and how retail business activities may be better organized within the context of omni-channel retailing to improve customer satisfaction.

Retail activities involve a dynamic supply-demand matching process, and omni-channel retailing includes both the integration of retail supplies at the company level and the fulfillment of retail consumer needs. It is an "intricate system that integrates various channels and resources to give consumers a seamless shopping experience" (Saghiri et al., 2017). The majority of research literature claims that omni-channel integration may reduce various customer purchasing costs (Li et al., 2018), improve retail matching efficiency (Liu et al., 2021), and boost customer satisfaction (Zhou et al., 2017), all of which can improve retail business performance. However, others have argued that during the process

* CONTACT: Mi Zhuang, email: miz_saber@outlook.com.
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of the integration of channels, consumers' cross-channel search raises their information costs (Rapp et al., 2015; Herhausen et al., 2015), impairs shopping experiences, and results in customer loss (Berry et al., 2010). Indeed in practice, firms who have embraced the omni-channel transition have not seen any meaningful improvement in company performance, raising questions about the omni-channel transition's economic relevance. A review of the relevant literature reveals that the majority of representative empirical studies have focused on measures of short-term corporate financial performance rather on long-term business performance. In this study, we use the indicator of CLV to investigate omni-channel retailing's impact on long-term business performance.

CLV is defined as the "profit brought by customers to businesses within their life cycle" (Berger and Nasr, 1998). According to Betancourt and Gautschi (1998), retail business output is jointly determined by businesses and consumers, and customers are vital to the evaluation of retail business activities, which is highly consistent with the management philosophy of CLV. At the theoretical level, CLV provides a theoretical criterion for evaluating retail firms' long-term business performance; at the methodological level, retailing as an important form of noncontract customer relations has become part of the discussion on CLV measurement (Cheng et al., 2019).

With the rising diversification of consumer requirements, it is vital for enterprises to improve the supply of goods and services based on a thorough understanding of customer needs. More detailed assessment of diverse consumer requirements also aids in the fine-tuning of marketing strategies for the deployment of omni-channel business models. Previous academic studies have examined heterogeneous consumers based on demographic (Carpenter and Moore, 2006) and psychological traits (Prasad and Aryasri, 2011), but these limited personal variables do not adequately capture consumer heterogeneity because retailing is a dynamic supply-demand matching process in which consumers make purchasing decisions when their diverse needs are matched with goods and services provided by retailers (Liu et al., 2023). In this study, we develop a basket of consumer items to reflect heterogeneous customer expectations and investigate how they affect omni-channel retail business performance.

2. Literature Review and Proposition of Hypotheses

2.1 Omni-Channel Retail and Economic Performance

Researchers have hitherto focused on the economic performance of omni-channel retailing (Verhoef, 2015). According to the majority of the literature, omni-channel integration reduces consumers' time, information, psychological, and logistical costs (Liu et al., 2018), increases retail matching efficiency (Liu et al., 2001), and improves retail business performance as a result of higher consumer satisfaction (Zhou et al., 2017). Other research literature has noted that during the process of online and offline integration, competition arising from intrinsic segmentation among retail channels may compel consumers to engage in cross-channel search (Rapp et al., 2015), increase consumers' information cost (Herhausen et al., 2015), and sully the consumer experience (Berry et al., 2010), resulting in consumer loss and crowding out of consumption among retail channels (Liu and Zhang, 2019). However, there has been a lack of empirical research on the omni-channel transition. Some sample empirical research has used customer survey data (Wu et al., 2017) or data from publicly traded Chinese retailers (Cui and Shi, 2021), and although the former is better suited to researching consumer behaviors than business performance, the latter cannot accurately reflect retail business performance because most retailers listed on the Shanghai and Shenzhen stock exchanges have a diverse business portfolio. Furthermore, previous studies have devoted little attention to assessments of omni-channel retailing's long-term performance. However, the available research literature focuses on the relationship among omni-channel retailing and short-term business performance even though according to its theoretical mechanism, omni-channel transition may improve shopping experiences and motivate consumers to repurchase, hence improving long-term retail performance. Short-term performance indicators, such as business revenue and gross merchandise value (GMV), cannot fully capture the mechanism of the omni-channel shift. As a result, long-term metrics of consumer repurchase rates must be used to determine how omni-channel transition influences retail business success.

2.2 Customer Lifetime Value

Customer value is a key indicator of long-term business performance and competitiveness (Woodruff, 1997a), and many scholars view it as a new source of corporate competitiveness (Woodruff, 1997b). To identify the most valuable customers, scholars began to analyze the amount of value that customers contribute during their lifecycle, also known as CLV (Berger and Nasr, 1998). CLV reflects long-term changes in consumer behavior, including repurchasing, and is an effective indicator of long-term business performance.

Since the calculation of CLV is dependent on the transactional relationship between enterprises and customers, identifying customer duration is a top priority in measuring CLV. Previously, scholars have classified transaction relations as contract or noncontract (Reinartz and Kumar, 2000) and developed algorithms accordingly. In the framework of our research, the transaction relations between retailers and consumers are typically noncontract. In the absence of a formal agreement, businesses lack visibility into customer attrition and must rely on historical data to make guesses about future purchase behavior (Cheng et al., 2019).

When measuring the lifetime value of noncontract customers, it is usual practice to develop a model for calculating CLV using their RFM traits[1]. Common types of model specification include the probability model (Schmittlein, 1987), the econometric model (Thomas et al., 2004), and the machine learning model (Coussement et al., 2010). However, the first two types of models are less effective at forecasting due to individual heterogeneity and consumer and corporate transaction characteristics (Reinartz and Kumar, 2003). In comparison, machine learning algorithms have grown in popularity among CLV researchers due to their high forecast accuracy (Cheng, 2019). For this reason, we use machine learning to predict CLV and also use the generalized additive model (GAM) and support vector regression (VAR) algorithms to provide robust results.

2.3 Omni-Channel Retailing's Effect on CLV

According to Betancourt (2016), the purpose of retail innovation is to recombine retail goods and services in order to reduce consumption costs such as time, shipping, adjustment, psychological, storage, and information costs (Betancourt and Gautschi, 1990). Omni-channel retailing can thus be defined as a process in which businesses use new technology to integrate online and offline channels and optimize retail supply in order to provide consumers with new portfolios of goods and services at lower transaction costs, while also improving the shopping experience and customer value.

Specifically, retailers may use digital applications to optimize retail matching and mobile Internet and big data analytics to help them interact with consumers, target consumers more accurately, and facilitate consumer searches for product information (Liu et al., 2022), thereby reducing consumers' information and time costs. In addition, the emergence of new business models such as forward warehouses and retail-to-home has shortened the physical shopping distance for consumers (Liu et al., 2021) and reduced shipping and storage costs. Furthermore, businesses may establish long-term and continuous relations with consumers by providing omni-channel services (Venkatesan et al., 2007). Continuous interaction can further enhance consumer perceptions (Wu et al., 2017), deepen brand impressions (Pentina and Hasty, 2009), continuously satisfy consumer expectations for seamless cross-

[1] RFM refers to recency, frequency, and monetary value (Fader et al., 2005).

channel experiences, and reduce their psychological costs. However, some studies have pointed out that channel integration is bad for the consumer experience (Berry et al., 2010) because they actually increase information costs (Herhausen et al., 2015), which tends to hinder the channel integration process. In the long run, omni-channel retailing may actually increase CLV together with long-term firm performance. Hence, we put forth our first hypothesis.

Hypothesis 1: Omni-channel shopping increases CLV.

2.4 Consumer Heterogeneity and Omni-Channel CLV

In the transaction demand matching process, heterogeneous consumer requirements result in retail supply differentiation (Ehrlich and Fisher, 1982), and firms must consider consumer preferences while supplying retail services and building marketing strategies (Qin et al., 2022). Omni-channel retailing is a new retail business model that offers consumers a smooth all-in-one buying experience via integrated online and offline channels, and it is vital to further know the characteristics of target consumers under this retail business model, as well as their shopping behaviors, in order to better understand the importance of omni-channel retailing to long-term business profitability. Based on the existing research literature and the realities of surveyed enterprises, in this paper we classify heterogeneous consumer requirements into five categories: Preference for diversity, sensitivity to contract performance costs, sensitivity to warehousing costs, sensitivity to information costs, and sensitivity to price. Then, each type of customer's effects on omni-channel CLV are examined.

First, diversity is a key determinant of consumer satisfaction (Ellickson, 2006) and a manifestation of improving consumption quality (Clements and Si, 2018). Under the omni-channel retail business model, online channels have broadened the shelf space of brick-and-mortar retailers and enriched the categories of commodities on display. Additionally, the deployment of digital systems has increased corporate supply chain efficiency. This allows retailers to adjust the structure and quantity of products on offer promptly (Hübner et al., 2016), and increase consumer satisfaction through algorithm-based recommendations. Thus, we propose the following hypothesis.

Hypothesis 2: Preference for diversity positively affects the impact of omni-channel retailing on CLV.

Second, the mobile internet has amplified the effect of contract performance and warehousing costs on consumer behavior. Consumer experience in online commerce can be influenced by contract performance costs such as delivery time and service level (Frischmann et al., 2012). By integrating online and offline supply chains, the omni-channel transition enables prompt delivery service based on consumers' locations and requests, reduces delivery time, lowers contract performance costs, and improves delivery service quality (Hübner et al., 2016). This encourages consumers who are concerned about the cost of contract performance to shop at omni-channel businesses. Thus, we have our next hypothesis.

Hypothesis 3: Sensitivity to the cost of contract performance positively affects omni-channel retailing's impact on CLV.

Third, the online retail business model encourages consumers to buy in bulk and retailers to sell in bulk in order to increase turnover ratios due to lower delivery costs and economies of scale. In this scenario, warehousing costs have become a key concern for customers. The omni-channel retailing business model has improved supply chain responsiveness through crowd-sourced shipping and other last-mile delivery modalities, which appeals to consumers who are sensitive to warehousing costs. As such, we propose the following hypothesis.

Hypothesis 4: Sensitivity to warehousing costs positively affects omni-channel retailing's impact on CLV.

Fourth, omni-channel retailing combines the three variables of "people, merchandise, and venue" with the use of digital technology, as well as information on consumers, products, and channels (Li

2014). Consumers may thus obtain consistent information about products, prices, and promotions without having to hunt for and compare information from many media. Furthermore, timely delivery of information via online means may lower adjustment costs. Therefore, we propose the following hypothesis.

Hypothesis 5: Sensitivity to information cost positively affects omni-channel retailing's impact on CLV.

Fifth, aggregated consumer spending equals the sum of monetary price and shopping cost, and retail services earn profits through specialized division of labor by lowering shopping costs for consumers (Betancourt and Gautschi, 1988), implying that consumers pay for lower shopping costs. However, due to economies of scale, retailers may reduce the average cost of service by increasing the size of their operations. In the long run, the total cost to consumers would then tend to decrease. Moreover, the omni-channel retail business model may improve the accuracy of promotional sales information (Liu et al., 2021), which would appeal to price-sensitive customers. Therefore, we propose the following hypothesis.

Hypothesis 6: Price sensitivity positively affects omni-channel retailing's impact on CLV.

3. Research Design

3.1 Sample Selection and Data Source

In this study, we used a large consumer data set from a prominent regional retail chain, denoted as "company H". The following considerations were factored in to choosing this sample enterprise. (i) Company H occupies a regional market monopoly, which allows us to control for the impact of industry competition. (ii) As a representative leader in business innovation, company H began implementing omni-channel retailing in 2016 and completed omni-channel business layout for the majority of its outlets by 2017.

We randomly selected 12,913 consumers who made purchases at company H from January 2017 to June 2019 and extracted all transaction records during this period, with each transaction record containing information on ten dimensions. Our data encompass all stores at company H with nearly 3 million shopping data points. With the company's support we also collected the demographic data of 3,000 consumers at company H through questionnaires, and after matching phone numbers from the questionnaires with the information in our data set, we obtained 2,399 matched consumer samples. During the data treatment process, all data were made anonymous, and all data collection was authorized by the company and agreed to by the consumers.

3.2 Variable Measurement and Model Specification

Variables employed in this study and their descriptions are shown in Table 1.

Table 1: Variable Explanations

Variable type	Variable name	Description
Dependent variable	CLV	Aggregate CLV, estimated with machine learning
Independent variable	Whether a consumer is an omni-channel consumer	Consumers with active consumption through online and offline consumption channels at company H are defined as "omni-channel consumers", and others are referred to as "non-omni-channel consumers"
Adjustment variable	Preference for diversity	Average number of different categories purchased per transaction
	Price sensitivity	Average discount per transaction

Table 1 Continued

Variable type	Variable name	Description
Adjustment variable	Sensitivity to the cost of contract performance	Percentage of high-contract-performance-cost items in a basket of items purchased per transaction; the higher the percentage, the smaller the sensitivity to the cost of contract performance[2]
	Sensitivity to warehousing costs	Percentage of high-warehousing-cost items in a basket of items purchased per transaction; the higher the percentage, the smaller the sensitivity to warehousing costs
	Sensitivity to information cost	Percentage of high-information-cost items in a basket of items purchased per occasion; the higher the percentage, the smaller the sensitivity to information cost
Control variable	Age and gender	Age is expressed in years; 0 represents male, and 1 denotes female
	Number of persons in consumer's household	Number of family members
	Annual income	Category variable: Numbers from 1 to 6 denote less than 30,000 yuan, between 30,001 and 80,000 yuan, between 80,001 and 120,000 yuan, between 120,001 and 300,000 yuan, between 300,001 and 1 million yuan, and above 1 million yuan, respectively

3.3.1 Explained variable

The explained variable is CLV, which was determined using machine learning through the following process.

(1) Forecasting basic sample facts. The following data collection was used for the measurement of CLV. We collected 30 months of company H's customer transaction data from January 2017 to June 2019. Referring to Cheng et al. (2019), we then undertook the following pretreatment of the data set.

(i) The monthly retail point of sale (POS) data was combined to calculate the overall monthly transaction value, consumption frequency, and average transaction value.

(ii) The data set was then divided evenly by time into two sample sets, referred to as Stage 1 and Stage 2. Stage 1 (the first 15 months) includes 6,324 consumer samples and 67,959 transactions, and Stage 2 (the latter 15 months) includes 12,205 consumer samples and 80,225 transactions. We employed Stage 1 data as independent variables and Stage 2 data as dependent variables to train GAM and support vector regression (SVR) models for estimating consumer CLV. Temporal segmentation into equal intervals can successfully reduce estimation bias caused by promotional events, festivals, and holidays.

(iii) Independent variables for estimation include RFM data, active months, and shopping channels. Among them, 70% of consumers in the first-stage samples were active for more than nine months, and as sample customers become more active, there is a rightward distribution of consumer transaction frequencies, indicating high data quality. Given the scarcity of consumption data used to anticipate CLV, we selected consumer transaction records with active months and monthly average consumption frequencies ranging from two to twenty times from Stage 1 samples for the construction of the models.

(2) Model training. CLV is the total amount of transactions made during the entire customer lifecycle and may be broken down into transaction frequency and average transaction value: $CLV=\widehat{F}\times\widehat{M}$. In this paper, we use generalized additive models (GAM) and SVR to forecast consumer transaction frequencies during the future active period, forecast the average transaction value per customer using the central limit theorem (CLT), and calculate the weighted average of CLVs estimated with these two algorithms based on their standard deviations to ensure robust results.

Step 1: Forecasting and evaluating consumption frequencies for the future active period. We used

[2] Since we use percentages to reflect sensitivity, the closer the sensitivity is to zero, the higher the sensitivity, which is somewhat counterintuitive.

the monthly average consumer transaction frequency of two-stage samples as the dependent variable, use RFM data, monthly consumption frequency, and active period T as independent variables, and introduced an interaction term to boost explanatory power. According to the data attributes, the GAM model uses a nonlinear smooth spline and constrained maximum likelihood estimation to avoid overfitting. For the Gaussian kernel function of the SVR model, we set $\varepsilon = 0.1$, *gamma* = (.5, 1, 2, 3, 4), and *cost* = (.1:100). Both models use 10-fold cross-validation to generate the final trained model. After the models were trained, they were used to produce the forecast values of monthly consumption frequency in Stage 2 and to evaluate model error by calculating the mean squared error (MSE). Specifically, the GAM model's MSE was 3.514, and the SVR's MSE was 3.673, indicating strong forecast accuracy.

Step 2: Estimating the expected average transaction value. The expected average transaction value was estimated using the sampling distribution of mean sample transaction values per customer based on the central limit theorem (CLT) (Schmittlein and Peterson, 1994). Specifically, the central limit theorem was employed to estimate the expected consumption value of each customer $M=E[\theta|Z_1,...,Z_x]$ based on the consumer's x historical transactions $Z_i(i=1,...,x)$. Here we assumed that the consumer's historical transaction $Z_{i\sim iid}N(\theta,\delta_W^2)$, and given consumer heterogeneity, we assumed that the average transaction value $\overline{Z}\sim N(E(\theta),\delta_A^2)$. Furthermore, consumer's average spending amounts were assumed to be independent from the transactions and other processes. Based on these above assumptions and the expected variance formula, we have:

$$M=E(\theta|Z_1,...,Z_x)=(\frac{X\delta_A^2}{X\delta_A^2+X\delta_W^2})\overline{Z}+(\frac{\delta_W^2}{X\delta_A^2+X\delta_W^2})E[\theta]$$

From this equation, the future average transaction value $\widehat{M}$ can be estimated using historical data so as to calculate $CLV=\widehat{F}\times\widehat{M}$. Finally, transaction data were employed to estimate the expected average transaction value to estimate the parameters δ_A=60.9 and δ_w=3652.58.

Step 3: Model training. Based on the trained GAM and SVR models, we estimated the consumption frequency of consumers within their expected active period from samples in the regressions set, calculated the overall forecasted value of transaction frequency using standard error as the weight to ensure robust results (Cheng et al., 2019), and then applied the conditional expectation model to estimate the average transaction value. Finally, the transaction frequency was multiplied by the average transaction value to estimate CLV. Figure 1 is the evaluation chart of the estimation model, which presents the respective forecast effects of the two models and the weighted average of forecast effects. The weighted model combines the respective advantages of the GAM model and the SVR model to adjust for forecast errors to some extent. Except for a few outliers, the weighted model provides a fair estimation of CLV. Hence, the weighted average model was adopted as the final estimation model. The descriptive statistical results for CLV estimation are shown in Table 3.

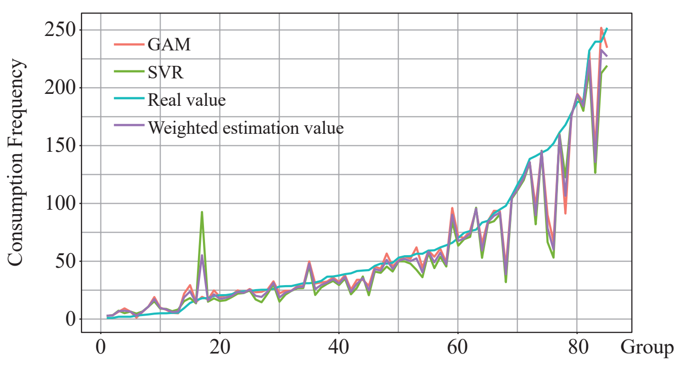

Figure 1: Evaluation Chart of Model Forecast Results

3.3.2 Independent variable

We define omni-channel retailing from a consumer's point of view. Consumers with active consumption in all online and offline consumption channels at company H were defined as omni-channel consumers. Hence, we created a binary variable where 0 denotes nonomni-channel consumers, and 1 refers to omni-channel consumers.

3.3.3 Adjustment variables

Based on Betancourt and Gantschi's (1998) definition of shopping cost and Liu et al.'s (2023) classification method, we identified five consumer preferences as mentioned below: Category preference, sensitivity to the cost of contract performance, sensitivity to warehousing costs, sensitivity to information cost, and price sensitivity. Category preference refers to consumer preference for the diversity of products in their shopping process, which is measured by the average number of categories per payment. Price sensitivity refers to the extent to which consumer purchase decisions are influenced by price and is measured by the average discount per payment. We measure sensitivity to the cost of contract performance, sensitivity to warehousing costs, and sensitivity to information cost according to individual product categories in accordance with the existing literature (Liu et al., 2023). For this we invited the representatives and experts from the target company for a discussion to classify company H's 25 primary product categories according to their cost of contract performance, warehousing costs, and information cost, and the results are shown in Table 2. Using this information, three categories of items as a share of consumption records were calculated. The higher the percentage of a certain type of commodity in the basket of commodities, the less sensitive consumers are to such costs.

Table 2: Classification of Commodities

Commodity characteristic	Product category
High cost of contract performance	Liquor and beverages, grain, edible oil and food products, delivery goods, refrigerated products, etc.
High warehousing costs	Baked goods, meat products, aquatic products, fruits and vegetables, etc.
High information cost	Pet products, apparels and accessories, furnishings, home appliances, imported goods, mother and baby products, etc.

3.3.4 Model specification

In order to test the effects of omni-channel retailing on CLV, we identify the omni-channel behaviors of retailers from a consumer's perspective. Based on the above variable specifications, our baseline model is specified below.

$$CLV_i = \alpha + \beta is.omni_i + \lambda Controls_i + \varepsilon_i$$

where the dependent variable *CLV* is CLV, *is.omni* means whether a consumer is an omni-channel consumer, and *Controls* is all control variables. Furthermore, we identify heterogeneous consumer requirements based on the characteristics of a basket of commodities from the transaction records in order to construct the adjustment variable model.

$$CLV_i = \alpha + \beta is.omni_i + \eta characters_i + \gamma is.omni_i \times characters_i + \lambda Controls_i + \varepsilon_i$$

where *characters* is consumer characteristic variables, and $is.omni_i \times characters_i$ is the interaction term between consumer characteristic variables and the independent variable; selection of variables is explained in the following section.

4. Empirical Analysis

4.1 Descriptive Statistics

Descriptive statistics for each variable are shown in Table 3. Among the consumer samples selected in this paper, the mean value of whether a consumer is an omni-channel consumer is 0.33. In the samples, nonomni-channel consumers account for a more significant share than omni-channel consumers since the sampled company is in the process of omni-channel retail transition. As can be found from the consumer preference variables, consumers are highly sensitive to cost of contract performance but less sensitive to information cost and price. A major reason for this is that most product categories in supermarkets are low-end daily necessities with a small price elasticity of demand.

Table 3: Descriptive Statistics of the Variables

Variable	Observations	Mean value	Standard error	Min.	Max.
CLV logarithm	2,399	6.58	1.07	4.23	8.89
Logarithm of forecasted consumption frequency	2,399	3.11	0.87	1.26	4.94
Logarithm of expected customer transaction value	2,399	3.46	0.43	2.18	5.27
Whether a customer is an omni-channel customer	2,399	0.33	0.47	0.00	1.00
Sensitivity to the cost of contract performance	2,399	0.62	0.16	0.00	1.00
Sensitivity to warehousing costs	2,399	0.45	0.18	0.00	1.00
Sensitivity to information cost	2,399	0.18	0.12	0.00	1.00
Diversity preference	2,399	3.28	2.09	1.00	22.72
Price sensitivity	2,399	0.11	0.06	0.00	0.64
Age	2,399	40.35	9.78	19.00	89.00
Gender	2,399	0.33	0.47	0.00	1.00
Number of family members	2,399	3.27	0.75	1.00	4.00
Income	2,399	2.79	1.16	1.00	6.00

4.2 Baseline Regression Results

The baseline regression results are shown in Model 1 of Table 4. The coefficient of the core independent variable ($\beta = 0.687$) is positive at the 1% level and means that omni-channel CLV is 68.7% higher than for nonomni-channel consumers, which supports Hypothesis 1. That is, the omni-channel consumers in our sample exhibited a stronger willingness to buy during their lifecycle, which provides empirical support to the existing research literature.

Models 2 through 7 present the estimated results after the variable of heterogeneous requirements was introduced. Compared to Model 1, Model 2's goodness of fit is about 13% higher, demonstrating the statistical effectiveness of the five heterogeneous requirements. Models 3 through 7 are the adjustment effect models, and the results of Model 3 suggest that the higher the level of consumer diversity preference, the higher the CLV of omni-channel customers, which supports Hypothesis 2. Results for Model 4 indicate that the higher the sensitivity to the cost of contract performance, the higher the CLV of omni-channel customers as well, which supports Hypothesis 3. Next, the results of Model 5 show that the higher the consumer sensitivity to warehousing costs, the higher the CLV of omni-channel customers, which supports Hypothesis 4. Model 6 shows that sensitivity to information cost has no significant adjustment effect, which runs contrary to Hypothesis 5. Finally, Model 7 reveals that price sensitivity has no significant adjustment effect, which is likewise contrary to Hypothesis 6. These results suggest that in the context of omni-channel retailing, retailers may provide consumers with more convenient services in terms of product categories, contract performance, and storage in order to increase CLV and boost long-term performance.

Table 4: Regression Results for Omni-Channel Consumers with Respect to CLV

Variable	Dependent variable: Logarithm of CLV						
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Whether a consumer is an omni-channel consumer	0.687***	0.642***	0.488***	0.940***	0.829***	0.634***	0.530***
	(-0.044)	(-0.041)	(-0.078)	(-0.171)	(-0.119)	(-0.08)	(-0.091)
Whether a consumer is an omni-channel consumer * Category preference			0.046***				
			(-0.02)				
Whether a consumer is an omni-channel consumer * Sensitivity to the cost of contract performance				-0.485*			
				(-0.27)			
Whether a consumer is an omni-channel consumer * Sensitivity to warehousing costs					-0.402*		
					(-0.24)		
Whether a consumer is an omni-channel consumer * Sensitivity to information cost						0.044	
						(-0.372)	
Whether a consumer is an omni-channel consumer * Price sensitivity							0.989
							(-0.723)
Sensitivity to the cost of contract performance		-0.083	-0.084	0.051	-0.103	-0.084	-0.086
		(-0.136)	(-0.136)	(-0.155)	(-0.137)	(-0.136)	(-0.136)
Sensitivity to warehousing costs		0.267**	0.265**	0.250**	0.373***	0.267**	0.273**
		(-0.107)	(-0.107)	(-0.108)	(-0.125)	(-0.107)	(-0.107)
Sensitivity to information cost		-0.610***	-0.611***	-0.593***	-0.619***	-0.622***	-0.604***
		(-0.184)	(-0.184)	(-0.184)	(-0.184)	(-0.21)	(-0.184)
Category preference		0.178***	0.164***	0.178***	0.179***	0.178***	0.178***
		(-0.009)	(-0.011)	(-0.009)	(-0.009)	(-0.009)	(-0.009)
Price sensitivity		-0.678**	-0.679**	-0.654**	-0.696**	-0.676**	-0.952**
		(-0.326)	(-0.326)	(-0.326)	(-0.326)	(-0.326)	(-0.383)
Gender	-0.029	-0.025	-0.023	-0.025	-0.025	-0.025	-0.025
	(-0.044)	(-0.041)	(-0.041)	(-0.041)	(-0.041)	(-0.041)	(-0.041)
Number of family members	0.131***	0.107***	0.107***	0.107***	0.108***	0.107***	0.107***
	(-0.027)	(-0.026)	(-0.025)	(-0.026)	(-0.026)	(-0.026)	(-0.026)
Income	-0.036**	-0.033**	-0.034**	-0.033*	-0.033**	-0.033**	-0.033**
	(-0.018)	(-0.017)	(-0.017)	(-0.017)	(-0.017)	(-0.017)	(-0.017)
Age	0.009***	0.007***	0.007***	0.007***	0.007***	0.007***	0.007***
	(-0.002)	(-0.002)	(-0.002)	(-0.002)	(-0.002)	(-0.002)	(-0.002)
Intercept term	5.660***	5.358***	5.410***	5.272***	5.327***	5.360***	5.389***
	(-0.136)	(-0.169)	(-0.17)	(-0.175)	(-0.169)	(-0.17)	(-0.17)
Adjusted R^2	0.104	0.232	0.233	0.232	0.232	0.231	0.232
Mean VIF	1.01	1.08	1.64	4.12	2.52	1.65	1.86
Sample size	2,399	2,399	2,399	2,399	2,399	2,399	2,399

Note: *, **, and *** indicate that the results of two-tailed test are significant at 10%, 5% and 1% levels. The same below.

5. Discussion

In order to explore the ways in which omni-channel retailing contributes to CLV further, we now decompose CLV ($CLV=\widehat{F}\times\widehat{M}$) into expected transaction frequency and expected average transaction value as dependent variables for separate regression analysis. Tables 5 and 6 present the regression analyses for the expected transaction frequency and the expected average transaction value, respectively.

Judging by these results, omni-channel consumers have a significantly higher expected transaction frequency and average transaction value. Compared to their nonomni-channel counterparts, these consumers had a 59% higher expected transaction frequency and a 5.2% higher expected average transaction value[3]. Among the preferences of various consumers, sensitivity to warehousing costs (β = 0.341) and category preference (β = 0.125) had significantly positive effects on the expected transaction frequency, and sensitivity to information cost (β = -0.422) and sensitivity to price (β = -0.632) had significantly negative effects on the expected average transaction value. In contrast, category preference has a significantly positive effect on the expected average transaction value (β = 0.053). Notably, sensitivity to the cost of contract performance has a significantly positive effect on consumption frequency (β = 0.214) with a significantly negative effect on the expected average transaction value (β = -0.297). This explains why there is no significant correlation between sensitivity to the cost of contract performance and CLV.

In the adjustment effect model with respect to the expected transaction frequency, the coefficient for "whether a consumer is an omni-channel consumer * category preference" is 0.064 and is significant at the 1% level, but none of the other adjustment terms has any significant adjustment effect on omni-channel consumers or expected consumption frequency. In the adjustment effect model of the expected average transaction value, the coefficient for whether a consumer is an omni-channel consumer * category preference is -0.018 and significant at the 5% level, and the coefficient for "whether a consumer is an omni-channel consumer * cost of contract performance" is -0.213, which is significant at the 10% level. The coefficient for "omni-channel consumers * sensitivity" to warehousing costs is 0.203, which is significant at the 10% level as well.

This reveals that with consumers' increasing diversity requirements, their future purchase frequency increases and future average transaction value decreases after they become omni-channel consumers. However, their future purchase frequency increases more sharply than their future average transaction value decreases, resulting in a more significant increase in CLV. After consumers less sensitive to the cost of contract performance and warehousing costs are converted into omni-channel consumers, they will thus likely generate a smaller growth rate of average transaction value compared to consumers more sensitive to the cost of contract performance, resulting in a smaller growth rate of CLV.

Hence, we find that omni-channel retailing increases CLV primarily by raising expected consumption frequency, which to some extent also increases the expected average transaction value. This process is adjusted by consumer preference for category, sensitivity to the cost of contract performance, and sensitivity to warehousing costs. Specifically, consumer preference for category positively adjusts omni-channel retailing's impact on the expected transaction frequency, and negatively adjusts the impact on expected average transaction value, but overall, consumer preference for category positively adjusts omni-channel retailing's impact on CLV. Both sensitivity to the cost of contract performance and sensitivity to warehousing costs positively adjust omni-channel retailing's impact on the expected average transaction value, creating a positive adjustment effect on CLV in the aggregate, as illustrated in Figure 2.

Table 5: Regression Results for Omni-Channel Consumers with Respect to Expected Transaction Frequency

Variable	Dependent variable: Logarithm of the expected transaction frequency					
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Whether a consumer is an omni-channel consumer	0.590***	0.375***	0.757***	0.683***	0.563***	0.523***
Whether a consumer is an omni-channel consumer * Category preference		0.064***				

[3] The β value in Model 1 was used.

Table 5 Continued

Variable	Dependent variable: Logarithm of the expected transaction frequency					
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Whether a consumer is an omni-channel consumer * Sensitivity to the cost of contract performance			-0.272			
Whether a consumer is an omni-channel consumer * Sensitivity to warehousing costs				-0.199		
Whether a consumer is an omni-channel consumer * Sensitivity to information cost					0.145	
Whether a consumer is an omni-channel consumer * Price sensitivity						0.591
Sensitivity to the cost of contract performance	0.214*	0.212*	0.289**	0.204*	0.211*	0.212*
Sensitivity to warehousing costs	0.341***	0.338***	0.331***	0.394***	0.340***	0.345***
Sensitivity to information cost	-0.188	-0.189	-0.178	-0.192	-0.227	-0.184
Category preference	0.125***	0.106***	0.125***	0.125***	0.125***	0.125***
Price sensitivity	-0.046	-0.047	-0.032	-0.055	-0.04	-0.21
Control variable	√	√	√	√	√	√
Adjusted R^2	0.125	0.227	0.222	0.222	0.222	0.222
Mean VIF	1.01	1.64	4.12	2.52	1.65	1.86
Sample size	2,399	2,399	2,399	2,399	2,399	2,399

Table 6: Regression Results for Whether a Consumer Is an Omni-Channel Consumer with Respect to Expected Average Transaction Value

Variable	Dependent variable: Logarithm of expected average transaction value					
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Whether a consumer is an omni-channel consumer	0.052***	0.113***	0.183***	0.146***	0.071**	0.007
Whether a consumer is an omni-channel consumer * Category preference		-0.018**				
Whether a consumer is an omni-channel consumer * Sensitivity to the cost of contract performance			-0.213*			
Whether a consumer is an omni-channel consumer * Sensitivity to warehousing costs				-0.203*		
Whether a consumer is an omni-channel consumer * Sensitivity to information cost					-0.102	
Whether a consumer is an omni-channel consumer * Price sensitivity						0.398
Sensitivity to the cost of contract performance	-0.297***	-0.297***	-0.238***	-0.307***	-0.295***	-0.298***
Sensitivity to warehousing costs	-0.074	-0.074	-0.082*	-0.021	-0.074	-0.072
Sensitivity to information cost	-0.422***	-0.422***	-0.415***	-0.427***	-0.395***	-0.420***
Category preference	0.053***	0.059***	0.053***	0.053***	0.053***	0.053***
Price sensitivity	-0.632***	-0.632***	-0.622***	-0.642***	-0.636***	-0.743***
Control variable	√	√	√	√	√	√
Adjusted R^2	0.023	0.112	0.111	0.111	0.11	0.11
Mean VIF	1.01	1.64	4.12	2.52	1.65	1.86
Sample size	2,399	2,399	2,399	2,399	2,399	2,399

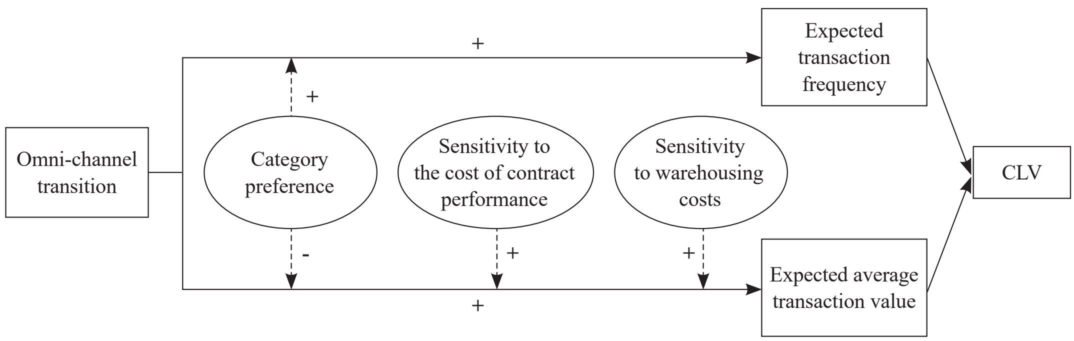

Figure 2: Contribution of Omni-Channel Transition to CLV

6. Concluding Remarks and Outlook

6.1 Research Conclusions and Implications

This paper used the CLV to measure the long-term business performance of an omni-channel retailer in China and performed an empirical analysis to examine several hypotheses related to the relationship between omni-channel retailing and CLV. We present the following conclusions. First, omni-channel consumers may generate a higher CLV, and omni-channel retailing may increase CLV by raising consumers' expected transaction frequency and average transaction value. Second, omni-channel retailing's effects on CLV are adjusted according to diversity preference, sensitivity to the cost of contract performance, and sensitivity to warehousing costs. Among these aspects, sensitivity to the cost of contract performance and sensitivity to warehousing costs both increase omni-channel retailing's impact on the expected average transaction value, thereby influencing CLV. Although consumer category preference diminishes omni-channel retailing's contribution to expected average transaction value, it still, by and large, increases omni-channel retail's contribution to production value per customer, because of its larger positive effect on consumption frequency.

This study supplements the theory of omni-channel retailing's contribution to corporate competitiveness from a long-term perspective by providing empirical evidence, and to some extent by addressing the inconsistencies between previous research conclusions. By establishing a correlation between the characteristics of actual commodities and consumers' heterogeneous requirements when shopping, we effectively broadened demand characteristics to more dimensions so as to support future insight into consumer behaviors. Our findings have the following business implications for retailers. First, the omni-channel retail business strategy may enhance consumers' omni-channel shopping experience, increase consumer stickiness, and assist retailers in acquiring a long-term competitive advantage amid increasingly fierce competition. Retailers, and especially brick-and-mortar retail stores, must embrace digitalization to survive and thrive. Second, omni-channel consumers are more sensitive to the cost of contract performance and to warehousing costs, and have a greater preference for diversity. Retailers should therefore design product categories and provide services accordingly.

6.2 Inadequacies and Outlook

Our empirical research has demonstrated the contribution of omni-channel retailing to CLV. However, there is still room to explore further in the following areas. First, differentiated retail supply is the result of adaptation to heterogeneous retail requirements, and our analytical framework and empirical rationale for omni-channel retail transition are applicable to all retail business models. Due to the limitation of our research sample, however, our conclusions may only be applicable to supermarkets. Future research may follow our analytical framework to analyze other retail business paradigms, and improve the mechanisms of omni-channel retailing and CLV. Second, CLV itself may reflect long-term business performance without revealing the cost of omni-channel transition. Provided that data are available, future research should further examine the relationship between omni-channel retailing and retail performance.

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