Hui-Hsin Huang

Associate Professor., PhD

Department of Advertising &Public Relations, Fu Jen Catholic University, Taiwan

Corresponding author:

e-mail: hoyasophia2020@gmail.com

ORCID: https://orcid.org/0009-0000-3442-3114

Published First Online:

20.12.2024

Pages: 245-253

DOI: https://doi.org/10.37075/JOMSA.2024.2.07

A MODEL OF PREDICTING CUSTOMER DEFECTION WITH SATISFACTION AND INTERPURCHASE TIME IN MARTECH FRAMEWORK

ABSTRACT

Customer defection is a major challenge for companies to remain competitive and profitable. This paper combines the variables of customers satisfaction and their interpurchase time to propose a statistic model of customer defection rate. The Bayer's rule is used for MarkTech application. The empirical data of customer purchase in E-commerce online platform are conduct for both parameters estimation and model calibration. The results show acceptable good fitness of proposed model and the practical data. The conclusion provides the suggestions for applying data combination with MarkTech.

KEYWORDS: Customer defection, Satisfaction, Interpurchase time, MarTech (Marketing technology).

JEL: M31, M37

INTRODUCTION

Since the marketing environment has rapidly changed in digitalization and online base marketing technology, MarTech (Marketing technology) is an emerging trend in marketing area. This trend causes digital ecosystem which combines Digital Marketing (DM) and Data Sciences (DS) to recognize the foundational of role of new technologies in diving marketing theory and practice (Hoffman et al., 2022). It also chage the way customers research products and make purchase which has led to an increase of customer touchpoints along the customer journey and a corresponding need for a richer set of digital tools that find and engage people on a global scale (Worthington, 2022). Hoffman et al. (2022) in Journal of Marketing define MarTech as "scientific knowledge and/or its application in the early adoption cycle for firms and/or consumers with the potential to influence the activity, institutions, and processes for creating, communicating, delivering, and exchanging offerings that have value for customers, clients, partners, and society at large".

Thus, one of the mean uses of data sciences in digital marketing strategies is tracking customer behavior online which is tracking and predicting consumer behavior on digital channels. In this way, companies can anticipate their advertising actions (Saura, 2021) and increase the profit and avenue from tracking customer repeat purchase and decreasing customer defection rate.

The topic of customer churn or defection behavior is always an important issue for company, when marketer wants to keep a constant market share (Somosi et al., 2022; 2021). Retention and defection are one with two sides and both of them are important variables to predict customer value. Most of the previous researches focus on the issue on customer retention and it's influenced factors such as customer satisfaction (Matuszelańskiand Kopczewska, 2022). Different from paying attention on retention, defection rate can help company to know the losing or lost customers and detect what reasons contribution this results immediately by signal or series specific marketing program (Mirkovic et al., 2022). To know the customer defection can turn unappropriated marketing strategy around. Comparing defection rate among competitors can also be a cornerstone for successful retention campaigns. Because to acquiring a new customer cost a lot than maintaining old one (Kim et al., 2020).
Thus, this paper proposed a statistic model of customer defection rate for MarkTech application. The article is organized as first, the literature review of MarkTech and customer defection are discussed. Then, the statistic model is demonstrated by probability distribution. The variables which construct this proposed model is also described in this section. Thirdly, the empirical data is introduced to make parameters estimation and model calibration. Finally, the results are shown and conclusion and discussion are made by the practice in MarkTech.

1. LITERATURE REVIEW

Marketing technology

A brief and practical definition of MarkTech is a range of software and tools that assist in achieving marketing goals or objectives. Different from AdTech which is strictly used to influence buyer behavior by promoting offerings, MarTech refers to technology that helps to create, communicate, and deliver offerings. Thus, another similar concept "CommTech" which is the use of digital technologies to not only execute but also manage communications along the whole stakeholder journey, ranging from monitoring touchpoints to evaluating stimulated action (Brockhaus et al., 2022).
Hoffman et al. (2022) demonstrated that it has received less attention in the literature is how new technologies, give rise to innovations in marketing techniques, tools, and strategies themselves. Thus, Journal of Marketing proposes a special issue of new technology in marketing to categorize new technologies impact marketing in four broads, first one is to support new forms of interaction among consumers and firms. The second is to provide new types of data that enable new analytic methods in marketing. And the third is to create marketing innovations. Finally, the fourth is to require new strategic marketing frameworks.
Brockhaus et al. (2022) sum up the previous researches into three topics which are the use of digital technologies for stakeholder relations in general (McLean et al., 2021), social media platforms and tactics in particular (Buhmann et al., 2021; Freberg, 2022; Lutrell et al., 2021; Wilson et al., 2020) and big data, automation and artificial intelligence (Buhmann and White, 2022; Moore and Hubscher, 2022).
Saura (2021) proposed a framework, methods, and performance metrics in digital marketing with using data sciences. In the framework, the type of methods used in data sciences as applied to digital marketing includes Bayer's rule which is used for the description of probabilities of events. It is based on knowledge about the conditions that could have caused a specific event. Therefore, this paper use Bayer's rule as the model construction and MarTech application.

2. CUSTOMER DEFECTION

The customer churn or defect to competitors may cause loss profit which directly contributes the corrosion of marketing revenue and market share for company (Zhang et al., 2022; (Mirkovic et al., 2022; Matuszelańskiand Kopczewska, 2022). Because keeping existing customers is cheaper than acquiring new customers (Kim et al., 2020). To manage the defection behavior can help companies reduce costs and optimize their budgets (Zhang et al., 2022). It is also a curial factor when discussing the customer lifetime value and customer loyalty in the customer relationship management (CRM) area.

For the purpose of this research is to develop a model of predicting customer defection rate, when reviewing past literatures, we categorize customer defection researches into two types: defection rate (or variable) application and model construction.

Some research applies customer defection as a key variable to predict customer purchase behavior such as Mesak et al. (2022) provide a diffusion models of subscription-based services which includes a customer acquisition process, a customer attrition process, and marketing-mix variables. The results show the defection of the first time customers could enhance a firm's profitability and advertising affects the coefficient of innovation, whereas price affects the coefficient of imitation.

Meire (2021) uses social media data to explore the defection customer coming back. links of Facebook likes and event attendances after defection with customer comeback are more informative than first-lifetime behavior. The comeback customers spend, on average, more than newly acquired customers, and lower-profile comeback customers reduce their spending with the firm upon return.

For model constructions, Xiahou and Harada (2022) based on the combination of k-means customer segmentation and support vector machine (SVM) which divides customers into three categories and determines the core customer groups to proposes a loss prediction model prediction. To compare these two approaches, the results show accuracy of the SVM prediction was higher than that of the logistic regression prediction. And k-means clustering segmentation is necessary because each prediction index after customer segmentation was significantly improved.

Lalwani et al. (2022) use AI technique with logistic regression, naive bayes, support vector machine, random forest, decision trees on train set and ensemble techniques are applied to see the effect on accuracy of customer churn prediction model. In hyperparameter tuning, K-fold cross validation has been used over train set. Finally, the approach of Adaboost and XGboost Classifier have highest accuracy than other approaches.

Zhang et al. (2022) use Fisher discriminant equations and logistic regression analysis to develop a churn prediction model to predict telecom client churn through customer segmentation. And they find the latter approach (he (logistic regression approach) performs better when building a telecom customer churn prediction model. This approach can predict churn behavior when customers are unsatisfied with the offered service.

For the literature review of model construction (Lalwani et al., 2022; Xiahou and Harada (2022; Zhang et al. 2022), it is finding that customer satisfaction is an important and most used index to measure customer experiments after purchase or use the service/ product online or offline (Zhang et al. 2022; Mirkovic et al., 2022; Matuszelańskiand Kopczewska, 2022). Customer satisfaction is conceptualized as the difference between optimal product performances a consumer ideally would hope for and the actual performance customer perceived (Carter and Dalal,2010; Huang, 2018). This point of view is called the ideal point theory (Carter and Dalal, 2010; Huang, 2018) it proposed the relationship shape between ideal performance and actual performance is like exponential distribution (Einhorn and Gonedes, 1976). Therefore, it is a dynamic process when customer has comprehensive experience during the whole purchase or service journey. The higher customer satisfaction causes low defection rate and achieve customer loyalty. Sand on this view of point, the customer satisfaction is considered as an impact factor which is involved in the defection model.

When discussing the model framing of defection, one curial variable that cannot be ignored is the customer interpurchase time (Bisset, 2022). Interpurchase time is often used to detect the customer who is still making transaction with the company or has switch to the competitor brands (Simon and Adler, 2022). To investigate customer lifetime value, interpurchase time is considered as one of the customers behavioral index which has customer behavioral implications and represents customer loyalty (Hasumoto and Goto, 2022). If the interpurchase time is longer than a period of time, it may mean the customer is defection (Hasumoto and Goto, 2022; Simon and Adler, 2022). Thus, interpurchase time is involved in the construction of customer defection model as one of impact variable.

3. THE MODEL

Based on the literature review, customer satisfaction and interpurchase time are two curial factors which are used to develop the defection model. We define T_i to be the i^{th} defection rate of the customer. It is included in satisfaction S and interpurchase time Q_i. The model is formulated as follows:

$$T_i = Q_i^{\alpha} \cdot S \qquad (1)$$

Then we can derive

$$\begin{aligned} D_i \equiv \log T_i &= \alpha \log Q_i + \log S \qquad (2) \\ &= U_i + N \end{aligned}$$

Where D_i, U_i and N respectively denote $\log T_i$, $\alpha \log Q_i$ and $\log S$. Let the c.d.f. of D_i be denoted by $F_{D_i}(\cdot)$ and the pdf of D_i, U_i and N be denoted respectively by $f_{D_i}(\cdot)$, $f_U(\cdot)$ and $g_N(\cdot)$.

Customer satisfaction

According to ideal point theory (Carter and Dalal, 2010; Huang, 2018), the satisfaction of the customer toward a particular brand is the distance between the ideal point and the actual performance and it follows exponential distribution (Carter and Dalal, 2010; Einhorn and Gonedes, 1976; Huang, 2018). Thus, we denote the satisfaction S is a random variable which follows exponential distribution and its p.d.f. is

$$f_S(s|\lambda) = \lambda e^{-\lambda s}, \quad s > 0 \qquad (3)$$

Then $\log S$ follows

$$f_{\log S}(y|\lambda) = \lambda \exp(y - \lambda e^{y}), \qquad y \in R \tag{4}$$

Geometric interpurchase time

The interpurchase time, denoted as Q_i, follows geometric density given by

$$f_Q(q|z, i, \tau) = z^{i}\tau \exp(-z^{i}\tau)q, \qquad q > 0 \tag{5}$$

We consider a Bayes model that the parameter z follows uniform distribution, where for given positive δ:

$Z \sim U(\delta, 1)$

$$f_Z(z)\begin{cases} = \dfrac{1}{1-\delta} & , \quad for \quad \delta < z < 1 \\ = 0 & , \qquad otherwise \end{cases} \tag{6}$$

The full model

The c.d.f. of D_i (see (2)) is given by

$$\begin{aligned} F_{D_i}(x) &= P(U_i + N < x) \\ &= \int_{\delta}^{1}\int_{0}^{\infty} P(U_i + N < x|U_i = q, Z = z) f_U(q|i, z, \tau) f_Z(z)\, dq\, dz \\ &= \int_{\delta}^{1}\int_{0}^{\infty} P(N < x - q) f_U(q|i, z, \tau) \cdot \frac{1}{1-\delta}\, dq\, dz \\ &= \int_{\delta}^{1}\int_{0}^{\infty}\int_{0}^{x-q} \lambda \exp(y - \lambda e^{y})\, dy\; f_U(q|i, z, \tau) \frac{1}{1-\delta} dq\, dz \\ &= \int_{\delta}^{1}\int_{0}^{\infty} \left[\exp(\lambda) - \exp(-\lambda e^{x-q})\right] f_U(q|i, z, \tau) \frac{1}{1-\delta} dq\, dz \end{aligned} \tag{7}$$

Where

$$\begin{aligned} f_U(q|i, z, \tau) &= \frac{d}{dq} F_U(q) \\ &= \frac{d}{dq} P(U_i < q) \\ &= \frac{d}{dq} P(\alpha \log Q_i < q) \\ &= \frac{d}{dq}\left[1 - \exp(-z^{i}\tau e^{q/\alpha})\right] \\ &= \frac{z^{i}\tau}{\alpha} \cdot \exp(-z^{i}\tau e^{sq/\alpha} + \frac{q}{\alpha}) \end{aligned} \tag{8}$$

Then

$$F_{D_i}(x)$$

$$= \int_{\delta}^{1}\int_{0}^{\infty}\left[\exp(\lambda) - \exp(-\lambda e^{x-q})\right] \; f_U(s|i, z)\,\frac{1}{1-\delta}\, dq\, dz$$

$$= \int_{\delta}^{1}\int_{0}^{\infty}\left[\exp(\lambda) - \exp(-\lambda e^{x-q})\right] \; \frac{z^i\tau}{\alpha}\cdot \exp(-z^i\tau e^{sq/\alpha} + \frac{q}{\alpha})\,\frac{1}{1-\delta}\, dq\, dz$$

$$= \frac{1}{1-\delta}\int_{0}^{\infty}\left\{\left[\exp(\lambda) - \exp(-\lambda e^{x-q})\right]\int_{\delta}^{1}\frac{z^i\tau}{\alpha}\cdot \exp(-z^i\tau e^{sq/\alpha} + \frac{q}{\alpha})dz\right\} dq$$

$$= \left[\alpha i(1-\delta)\tau^{\frac{1}{i}}\right]^{-1}\int_{0}^{\infty}\left[\exp(\lambda) - \exp(-\lambda e^{x-q})\right]\exp\left(\frac{-q}{\alpha i}\right)\left[IG(\frac{1}{i}+1,\, \tau e^{q/\alpha}) - IG(\frac{1}{i}+1,\, \delta^i\tau e^{q/\alpha})\right] dq \qquad (9)$$

Where $IG(\frac{1}{i}+1,\, \tau e^{q/\alpha})$ and $IG(\frac{1}{i}+1,\, \delta^i\tau e^{q/\alpha})$ are incomplete gamma.

$IG(\frac{1}{i}+1,\, \tau e^{q/\alpha}) = \int_{0}^{\tau e^{q/\alpha}} v^{\frac{1}{i}}\left[\exp(-v)\right]dv$ and $IG(\frac{1}{i}+1,\, \delta^i\tau e^{q/\alpha}) = \int_{0}^{\delta^i\tau e^{q/\alpha}} u^{\frac{1}{i}}\left[\exp(-u)\right]du$

Finally, we have the following p.d.f. of D_i

$$f_{D_i}(x) = \frac{d}{dx}F_{D_i}(x)$$

$$= \left[\alpha i(1-\delta)\tau^{\frac{1}{i}}\right]^{-1}\times$$

$$\int_{0}^{\infty}\exp\left(\frac{-q}{\alpha i}\right)\cdot\left[\exp(\lambda) + \lambda\exp(x - q - \lambda e^{x-q})\right]\cdot\left[IG(\frac{1}{i}+1,\, \lambda e^{s/\alpha}) - IG(\frac{1}{i}+1,\, \delta^i\lambda e^{s/\alpha})\right]dq \qquad (10)$$

4. THE EMPERICAL DATA

The empirical data is from E-commerce online planform which is the emerge Martech practice conduct in their customer detection and use behavior prediction.

The customer data included the information for 5237 clients from 2021 to 2022, as well as anonymous demographic information, transaction mometary, interpurchase time, postpurchase comments, the item of purchase and its volums. We use the data of postpurchase comments as the satisfaction data which is evaluated after receiving the ordering. The online system will ask customers to give a common from “one star” to “seven stars”. More stars customer gives demonstrate more satisfaction he or she feels. The interpurchase time is collected by days. The below table shows the description of satisfaction value, interpurchase time and number of transactions which is represent the order times(i).

Table 1. Details of data description

	Interpurchase time	Satisfaction Value	Number of Transactions (Order times)
mean	10.506	3.023	8.997
Max.	63.259	7	48.235
Min.	5.245	0	3.420

We use half of the data (2618 clients' data) for parameters estimation and another half of the data (another 2619 clients' data) for proposed model calibration.

The parameters estimation

We use MLE (maximum likelihood estimate) to estimate the parameters. Let t_{ih} denote the monetary spending by customer h at the ith interpurchase time. And let L_i denote the likelihood of the monetary spending at the ith interpurchase time, that is:

$$L_i(\lambda, \tau) = \prod_{h=1}^{n} f_{T_i}(logt_{ih})$$

Let L denote the total likelihood. Then

$$L(\lambda, \tau, \alpha) = \prod_{i=1}^{m} f_i(\lambda, \tau, \alpha) = \prod_{i=1}^{m}\prod_{h=1}^{n} f_{T_i}(logt_{ih})$$

Then,

$$\prod_{i=1}^{m}\prod_{h=1}^{n} f_{T_i}(logt_{ih})$$
$$= \left[\alpha i(1-\delta)\tau^{\frac{1}{i}}\right]^{-mn} \times$$
$$\int_0^\infty exp\left(\frac{-mnq}{\alpha i}\right)[exp(\lambda) + \lambda exp(x - q - \lambda e^{x-q})]^{mn}\left[IG\left(\frac{1}{i}+1, \lambda e^{S/\alpha}\right) - IG\left(\frac{1}{i}+1, \delta^i \lambda e^{S/\alpha}\right)\right]^{mn} dq$$

(11)

We differentiate L (λ, τ, α, δ) respectively regarding λ, τ, α, δ and set them equal to zero.

The results

The results of parameter estimation is shown in table 2.

Table 2. The result of parameter estimates

λ	τ	α	δ
3.412	11.325	0.0325	0.1245

The results show the parameters of satisfaction(λ**)** and interpurchase time(τ**)** is closed to the mean of these two values which demonstrates that the proposed model is similar to the empirical data from. And the power term of interpurchase time(α)is positive. It means the interpurchase time is larger with the period of time goes by.

For the model calibration, RMSD (Root-mean-square deviation) is used to caclute the difference between model gerneration data and the empirical data. The result show RMSD is 0.4032 which is lower than 50%. Thus this proposed model is acceptable good fitness to describe the actual dataset.

CONCLUSION

This paper proposes a stochastic model of defection rate with conbining customer satisfaction and his (her) interpurchase time. This prposed model sucuessfully linke the customer behavioral data and perceivd data to show acceptable good fitness of model. In the previous, it is usasully to use survy to investaige customer satisfaction. But in the MarTech aera, the commons from customer feedback after online purchase is a immediately and accurate to obtain customer perceive experiment. Through MarTech the percieve data can translate to behavioral data form which is easilier and available from the customer database system.

The defection rates are an important index which may threaten company profit and increase marketing cost. This model provides a suggestion for company in high customer defection with adjusting the level of customer satisfaction and the interval of interpurchase time. In the future, other type of probability distribution can be considered. And other impact factors such as word of mouth can be involved to detect customer defection model.

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