Title: The Habitual Behaviour of the Online Customer

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1 Abstract

With the liberalisation of the Indian economy, there is an increasing adoption of technology to aid daily living. The internet is one such technology that has changed the way people shop in India. Multiple studies, by Industry bodies and consulting companies, have indicated a steady and possibly exponential increase in the adoption of e-commerce and online retail in India, backed by an almost steady inflow of investments from PE and VC funds into e-commerce and allied services. The average online spend per customer has also seen a stable increase from USD 127 in 2013 to USD 247 in 2015 to USD 464 (projected) in 2020. Despite this, there is not much of academic literature in the Indian context. Anecdotal evidence, from industry reports suggest that consumption pattern are increasingly moving away from functional needs to lifestyle consideration. This is yet to be tested empirically.

Studies have established the profitability of retaining customers and the importance of understanding and linking the demographic profiles of customers to behavioural pattern. In this study, we make an attempt to understand the antecedents of behavioural loyalty for customers shopping online for groceries in India.

The focus of our study was the grocery category, generalizable to low-involvement products. We obtained the anonymised transaction history of about 8000 customers from an online grocer. We developed a habit score based on literature to measure habit and included it in the Latent Growth Curve Model along with the other identified exploratory variables. In the Latent Growth Curve model we clearly saw that with the inclusion of the habit score, the model fit indices improved from poor to good and the presence of the habit score explaining a good percentage of the variance in the buying behaviour.

Keywords:

Online retail, etail, consumer behaviour, loyalty, repeat purchase, habit.

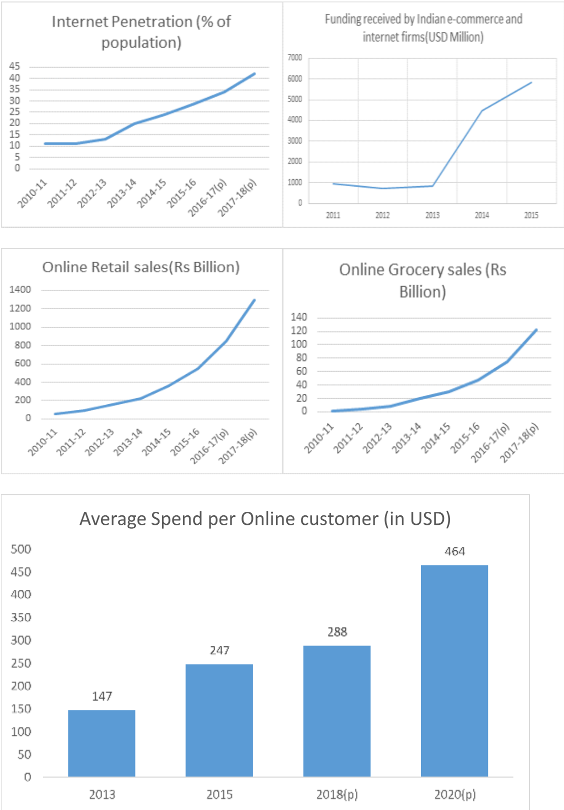
2 Introduction and Objectives

According to the Sixth Economic Census (2013-14), Government of India, the Indian retail industry accounts for over 10 per cent of the country's Gross Domestic Product (GDP) and the retail trade accounts for about 27.19 million persons (20.7% of employment). According to the A.T Kearney's Retail Development Index, the Indian retail trade was growing at a CAGR (Compounded Annual Growth Rate) of 8.8%, in the years 2013-2015 and the total annual retail sales was estimated to be about USD 1.01 trillion.

5.3 E-Commerce and Online Retail in India

The charts given below (Figure 3) give a broad over-view of the growth of online retail in India.

Fig 3: Overview of the growth of online retail in India



Source: www.ibef.org, ASSOCHAM, IAMAI,World Bank, Nielsen India

5.3 Online Fruits and Grocery Market in India

According to the Technopak 2016 report, the share of Food and Groceries (F and G) is less than 1% of the e-tail market and is projected to be about 5% by 2020. The market, according to the report, is dominated by 3 large players, Bigbasket, Grofers and Amazon and is largely concentrated in the top 8 metro cities of India. According to Tracxn, as on December 2016, there were about 450 grocery delivery start-ups in India. Together, these companies have raised about USD 450 million from investors in 2016. It is in the stated overall context of the Indian online retail ecosystem that we would like to study some important factors that would help us better understand repeat purchase and customer loyalty in the online retail industry.

3 Literature Review

Srinvasan et al (2002) and Anderson and Srinivasan (2003), defined e-loyalty as the customers' favourable attitude that led to repeat buying behaviour. Some of the antecedents to e-tail loyalty presented in literature include,

- Customisation (Schrage, 1999 and Kahn 1998)
- Interactivity (Deighton 1996, Alba 1997,Watson, Akselsen and Pitt, 1998),
- Customer service- characterised by the quality of service and effective prevention and management of service failure (Hoffman and Davis 1993, Rust and Zahorik 1993, Bolton and Drew 1993, Boulding, Kalra, Staelin and Zeithml,1993)
- Product Variety and choice (Alba 1997)
- Convenience (Alba 1997, Cameron 1999, Schaffer 2000)
- Trust (Dwyer 1987, Gronroos 1990, Hewett and Bearden 2001, Harris and Goode 2004, Flavian 2006)

Literature also indicates that there is a differential behaviour in terms of the drivers for repeat purchase for low-involvement and high-involvement products. (Fang (2014), Mayer (1995) Schlosser (2006), Holmes (1991), Vellido, Lisboa and Meehan (2000))

Nature of Grocery Products and Grocery Shopping

Marketing literature has widely acknowledged that the nature of the product influences the way consumers shop for the product. (Copeland 1923) based on the usage, purchase frequency and the price, classified goods as Convenience, Shopping and Speciality products. (Rothschild 1984, Laurent and Kapferer 1985, Mittal and Lee 1989) classified products based on the level of product involvement and shopping involvement. Based on the degree of knowledge required to understand the various features of the products, products are categorised into 'Search', 'Experience' and 'Cadence' (SEC) products (Nelson 1970 and Darby and Karni1973, Klein 1998).

Groceries have been classified in literature as:

- Low-involvement (Knox and Walker (1995).
- Search products (Girard, Korgoankar and Silveblatt (2003, 2006))

Necessary, repetitive, perishable with a low volume to weight ratio Morganosky (1997), Raijas and Tuunainen (2001), Brithwistle (2006) due to which the shopping for food and groceries cannot be similar to other shopping experiences.

Literature has largely found grocery shopping to be goal oriented and functional (Sheth (1983) and Dholokia (1999), required less cognitive effort (Deshpande and Hoyer (1983), an unavoidable, routine, boring necessity, and a chore (Buttle and Coates (1984), Geuens (2003), Dholokia (1999), Aylott and Mitchell (1998) and Aylott and Mitchell (1998).

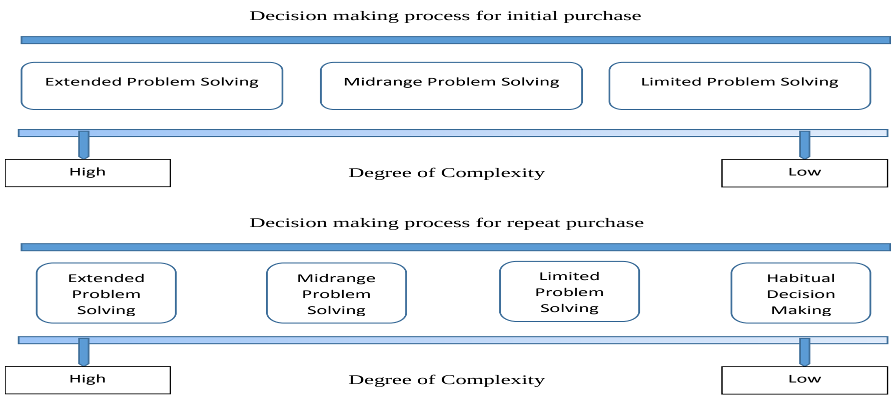
Many researchers also found grocery shopping to be largely habitual in nature ((Hoyer, MacInnis and Pieters (2013), Dijksterhuis, Smith, Baaren & Wigboldus (2005), Melis, Lamey and Breugelmans (2016), Urbany, Dickson and Kalapurakal (1996)). Consequently, researchers also fund grocery shopping to be stressful and found multiple stressors – crowding, queuing, and under-staffing (Wicker (1973), Matthews (1995)), Urbany, Dickson and Kalapurakal (1996)) time-pressure (Ajami (1994)), Park, Iyer and Smith (1989), Dickson and Kalapurakal (1996).

With this in the backdrop, we now present some of the theories that could explain the grocery shopping behaviour, the choice of online channel for grocery shopping in specific and the shopping behaviour of low-involvement products in general. While keeping the store choice process in the backdrop, our specific focus will be on presenting theory that explains repeat purchase behaviour.

The Nicossia (1966), Howard-Sheth Model (1969), Engel,Kollat and Blackwell (1968), largely based on the information search concept, that explained how the customers searched for information prior to making a purchase and the impact of the information search process on the final purchase choice. Another set of models, Theory of Reasoned Action ((Fishbein and Ajzen, 1975) and Theory of Planned Behaviour (Ajzen, 1985), suggested that the consumers' behaviour is determined by their intention to perform that particular behaviour.

Miniard, Blackwell and Engel, taking a problem solving approach to consumer decision making, considering the complexity of the problem, classified the purchase decision making into the continuum:

Fig 9: Consumer Decision Making Continuum



Source: Engel, J. F., Blackwell, R. D., & Miniard, P. W. (1995). Consumer behavior, 8th. *New York: Dryder*.

From the continuum, it is clearly seen that the decision making process for repeat purchases of products that are of low complexity tends towards the habitual decision making bucket.

Low Involvement products, where purchases are routine in nature are amenable to habitual decision making and are likely to induce a choice inertia in the customers. The customers are likely to develop a heuristic based on their previous purchases and are likely to make a satisficing choice. Once the choice is made, the customer will need a compelling reason to move away from the choice made (inertia) and in case the customers do need to make a different choice, they are likely to evaluate the heuristic chosen to make the choice rather than the choice per se. (Deshpande, Hoyer and Jeffries (1982), (Klien and Yadav 1989, Payne, Bettman and Johnson 1988)).

5.3 Repurchase, Loyalty and Habit

Uncles, Dowling, and Hammond (2003) summarised the various definitions of loyalty as:

- Loyalty as an attitude that leads to a relationship with the brand
- Loyalty expressed in terms of revealed behaviour (pattern of past purchases)
- Buying moderated by the individual's characteristics, circumstances, and/or the purchase situation.

Oliver (1999), defines loyalty as a "deeply held commitment to rebuy or re-patronize a preferred product or service consistently in the future, thereby causing repetitive same brand or same brand-set purchasing, despite situational influences and marketing efforts having the potential to cause switching behaviour." According to Oliver (1999), consumers become loyal at many phases, first in a cognitive sense – where the customer becomes loyal to the brand based on the available information, then in an affective sense – loyalty based on the cumulative satisfactory usage of the product or service, later in a conative manner – the increasing affective loyalty leads to a positive behavioural intention, and finally in a behavioural manner, when the customer acts on the previously built up behavioural intention and repurchases the product or the service. Oliver (1999), like other researchers, Brakus, Smith, Zarantonello (2009), Sinha and Banerjee(2004), Dick and Basu (1994), have used brand synonymously with services providers, such as retailers, coffee shops, hotels and others, too.

In our research too, we use the theoretical foundations of brand loyalty to understand and model the repeat purchase behaviour. The online store (the online grocery store, in our case) is treated as the focus of the repeat purchase and the unit of analysis. We do not delve into the contents of the basket or the specific product and brands that were purchased.

Wood, Quinn and Kashy(2002) defined habits as "those behaviours that were performed frequently, were done in a stable context, were not very complex to perform, did not require much thought to perform, and were explained in terms of external causes than internal ones."
Thompkins and Tam (2013), define habit as "behavioural disposition that is exercised frequently and in which responses are triggered directly from contextual cues".
Wood and Neal (2009) have associated four types of contextual cues to the development of habit

1. Time
2. Location
3. Social setting
4. Preceding or ensuing event

The authors of this paper differentiate habit from attitudinal loyalty, suggesting that attitudinal loyalty is motivated by favourable attitudes at the brand level and habit being associated with the presence of stable cues at the purchase context level. Oliver (1999), Johnson, Herrman and Huber (2006) attribute the formation to favourable attribute towards a brand to factors such as satisfaction and perceived value. Lally (2010) attribute the formation of habits to associative learning and repetitive behaviour in the presence of a consistent contextual cue. Duhigg (2012) also emphasise that the only sufficient condition for the formation of a habit is the presence of a stable context and repetitive behaviour. While Thompkins and Tam (2013) discuss the possibility of some overlap in the formation of habit and attitudinal loyalty, and discuss cases where attitudinal loyalty motivates purchase and in the presence of contextual cues, it becomes a habitual behaviour. In some cases, habitual behaviour could be a precursor to habit. And in cases where attitudinal loyalty and habit develop in parallel, the presence of contextual cues ensure both loyalty and habit persist together. However, the presence of contextual cues is a necessity in any of the mentioned cases. Literature indicates that habit formation is likely to occur with the presence of a goal that is not very complex in its nature, which is routine and simple, and repetitive in nature in a stable context or in the presence of situational factors. We would like to use this basis to form an empirical model for grocery purchases, since from literature presented earlier, grocery purchase is likely to fulfil most of the above mentioned criteria. (Verplanken and Aarts (1999), Reibstein (2002), Limayem, Hirt & Cheung (2007), (Wood (2002), Tam and Thompkins (2013)

5.3 Gaps Identified in the Literature

In this section, we present the gaps in literature that we have identified that we propose to address.

Understanding the purchase behaviour of customers

Most studies mentioned in our literature have used perceptual scales for measuring the intention to purchase online, as stated by Vellido, Lisboa, and Meehan (2000). Vellido,Lisboa,and Meehan summarised the literature studying the motivation of online purchase as thus - attitudes towards online shopping were influenced by product perception, shopping experience and perceived risk/trust while the *'intention to shop online'* was influenced by customer service, product perception and shopping experience. Other researchers too have also pointed out the need to study the actual behavioural data. Beck, L., & Ajzen, I. (1991), Wang, Harris, Patterson (2013), Shim et.al (2001), (Ngobo 2011), Jiang and Rosenbloom (2004).

Context Specific research

In the Indian context, as of today, we have a broad over-view of the differential behaviour of various demographics of customers and purchase behaviour. These inferences have largely been derived from proposals from various periodic industry reports and newspaper surveys. While the conclusions are intuitively acceptable, these need to be verified based on rigorous statistical procedures.

Sinha (2003), Sinha and Uniyal (2005), Kaur and Singh (2007) and Gehrt, Rajan, Shainesh, Czerwinski, and O'Brien (2012) and a few other researchers have developed psychographic measures to understand the shopping behaviour of customers. But these is no research modelling behavioural data. According to Rama Bijapurkar (2013,2014), consumer India is a unique evolving story that needs to be understood, while avoiding a mind-set and a dominant logic, that is driven by "…..a phenomenal aspiration for a better life is confronted by a spectacular failure of public goods; or to consumers expectation of service when high-touch and high-tech coexist in supply-side service offering….". This puts Indian consumers in a unique position and existing academic literature do not seem to consider this uniqueness.

Anecdotal evidence, from industry reports suggest that consumption pattern are increasingly moving away from functional needs to lifestyle consideration. This is yet to be tested empirically.

Antecedents to repeat purchase

While multiple studies have focussed on the variables such as convenience, customer service, price and others as being the drivers of loyalty and repeat purchase, a clear understanding of relevance and importance of habit in repeat purchase behaviour is not extensively explored and this is of importance since studies, as mentioned earlier, have established that the link between the behavioural intention and the actual behaviour weaken in the presence of contextual factors and habit.

4 Research Question and Hypothesis

Based on the literature survey and the identified research gaps, our research objective is to build a theoretical model for understanding the repeat purchase behaviour of online customers in a low-involvement, specifically grocery products, context.

5 Method

5.3 Selection of Variables for inclusion in the study

Table 3: Selection of Variables for the study	
Variable	Paper
Total Order Value	Schmittlein and Peterson (1994);Lemon (2002),Buckinx and Poel(2005);
Average Order Value	Bhattacharya (1998), Mozer (2000), Popkowski (2000),Buckinx and Poe (2005)
Number of Orders	Bhattacharya (1998), Mozer (2000), Popkowski (2000),Buckinx and Poe (2005)
Average Number of Days Between Orders	O Brien and Jones (1995), Wu and Chen(2000)
Types of Payment Methods used	Buckinx and Poel(2005), Sambandam and Lord(1995)
Complaints Raised	Buckinx and Poel (2005), Reichheld and Sasser (1990)
Length of Relationship	Bhattacharya (1998);Verhoef (2002);Bucknix and Poel (2005)
Deal-proness	Bawa and Shoemaker (1987);Kim and Staelin (1999)
Demographic variables – Age, Gender, Affluence	Donthu and Gracia (2001), Girard, Korgaonkar and Silverblatt (2003) Kau, Tang and Ghose(2003)

5.3 Sources of data used in the study

Sl.No	Data	Source
1	Customer transaction history	Internal transaction database on the online grocer.
2	Customer demographics	Online grocer's internal records
3	Delivery Issues raised by the customer	Online grocer's internal records

4	Retail access in the delivery location	Online classifieds service providers and IMRB research
5	Property prices in the delivery location	Department of Registration and Stamps
6	Advertisements issued by the company on radio	One of the two television and radio audience measurement analysis in India.

5.3 Method of analysis and model development

According to Tam and Thompkins (2013), habit could be a major contributor to the development of behavioural loyalty, and the existence of habit could be with or without the existence of the attitudinal component of loyalty. In our study, we consider only the behavioural elements of loyalty and do not study the other aspects of loyalty.

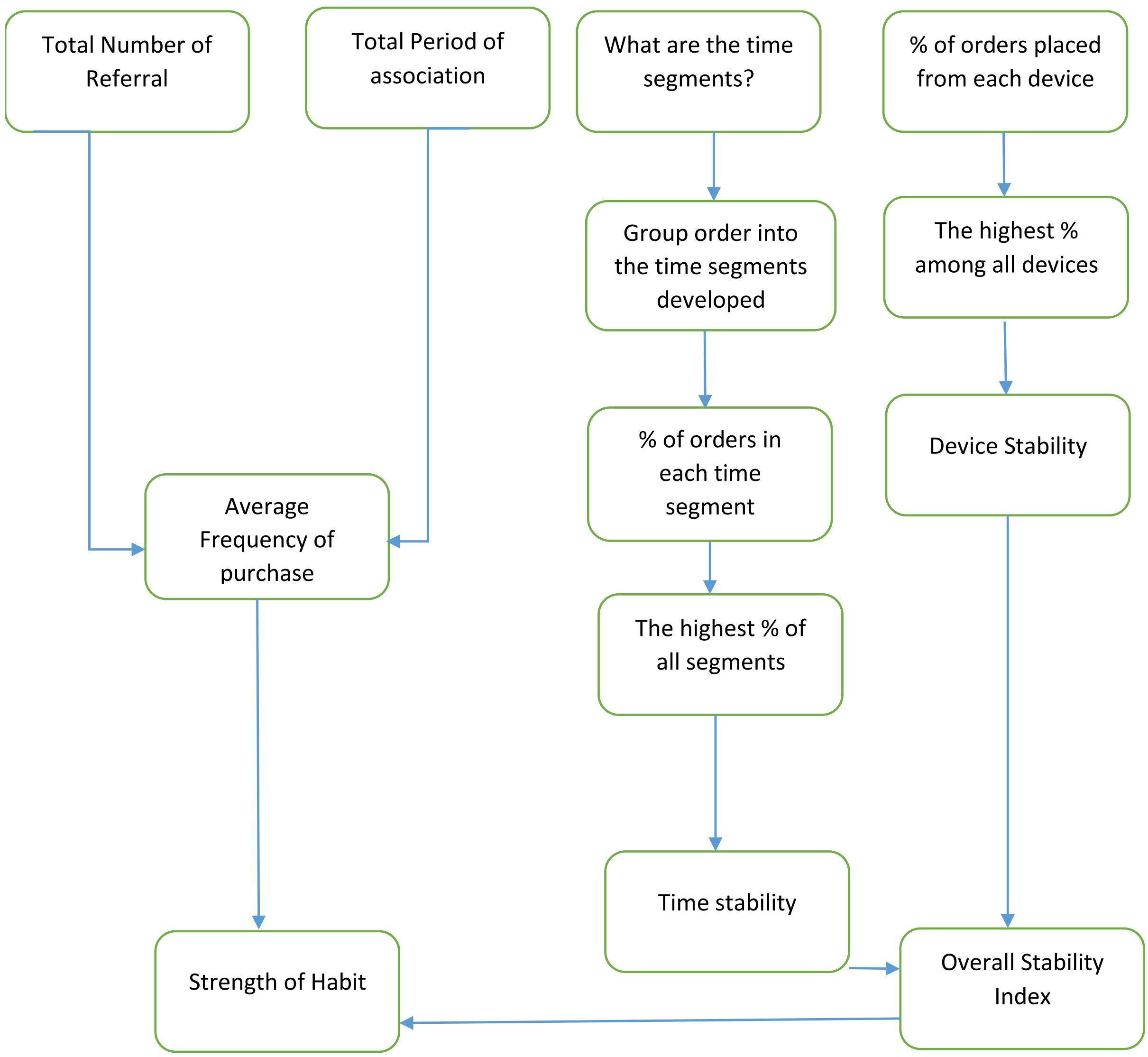
Tam and Thompkins (2013), define habit, based on the definition given by Wood and Neal (2009) as:

“Behavioural disposition that is exercised frequently and in which responses are triggered directly from contextual cues”. Contextual cues include:

1. Time
2. Location
3. Social setting
4. Preceding or ensuing event

The existence of two of the contextual cues are considered necessary to trigger habit. For the purpose of our analysis, we consider time and location to develop the model. Our study is of online grocery customers and our methodology is based on empirical analysis of the past purchase behaviour recorded in the transaction database of the company, we could hence not measure the social setting and the preceding or ensuring event of purchase. We also did not have access to the detailed log files, that could give us an indicative record of the IP address, the browser and other such variables which could be possible proxy indicators of the social setting or the click steam data (up-stream and down-stream clicks) that could be indicative variables of the preceding and ensuing event. We hence choose time (date of purchase) and device (PC, Mobile, and Telephone) used to make the order, to develop the habit score. Wood, Quinn and Kashy (2002) consider the time and location of purchase as being the most effective variables in determining habit.

Based on the above definition and the conceptualisation of habit score by Tam and Thompkins, we illustrate the development of habit score, built on action frequency and contextual stability, in the image given below:



This consists of the time and device stability variables. We developed the index as follows:

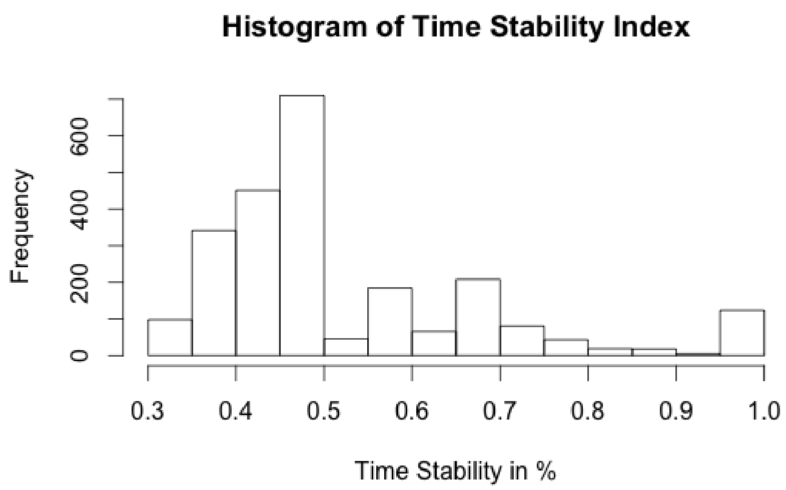
Time Stability Index

We grouped the customers based on time period in which the order was placed as

- Group 1 – orders between 1st and 10th of the month
- Group 2 – orders between 11th and 20th of the month
- Group 3 – orders between 21st and 30/31st of the month

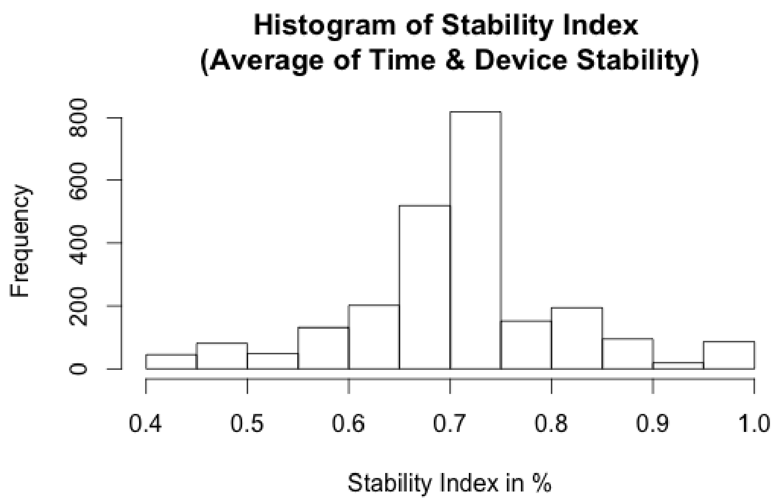
This grouping of customers, in absence of academic literature in the Indian context, was based on the inputs given by the company.

We then calculated the percentage of customers' transaction that occurred during each group and chose the highest percentage for each customer to represent the time stability. If a customer has an order in each of the 3 groups, for example, her time stability score would be 0.33 while a customer with all 3 purchases in one group would have a stability score of 1.00. The histogram of the time stability index is given below. The time stability histogram indicates that the index is mostly concentrated around the lesser than the 50% mark, ranging from 33% to 100% suggesting that the customer orders are scattered through the month and there seems to be less stability in the time of purchase. This is in line with the earlier analysis that we presented in chapter 5.



Device Stability Index

The data for the device used was shared with us by the company, against each order, based on the user interface from which the order was placed (web interface/phone-app interface/tab-interface) .To develop the device stability index (Mobile Phone, Tab, Laptop were the devices under consideration), we grouped the customers based on the device from which the order was placed and calculated the percentage of customer orders that occurred in each group. The stability index ranged from 40% to 100%, with the median around 70%, indicating a higher stability of the device from which the order is placed. The histogram of the device stability index is given below:



Based on Tam and Thompkins (2013) and Wood, Tam and Witt (2005), we developed the overall stability index by considering the average of the device and the time stability index. We then developed the habit score by multiplying the average monthly purchase with the stability index. The habit scores ranged from 0.0833 to 2.375. We have presented the individual habit score for each customer in the Appendix. The other variables that we have used for the development of the model are:

1. Gender (Gen)
2. Age of the customer (Age)
3. Association Days (Assoc)
4. Spending Relative to the length of the customer relationship (Spendrel)
5. Average Order Value(aov)
6. Number of complaints raised (compl)

7. Number of vouchers used (voch)
8. Mode of payment (paym)
9. Std.deviation of interpurchase time (stdinter)

We then fitted the habit score, along with other independent variables into the LGC modelling framework to understand the impact of these variables on behavioural loyalty.

According to Curran and Hussong (2002, p.65), "The SEM approach (to analysis of repeated measures data) simultaneously estimates relations between observed variables and the corresponding underlying latent constructs and between the latent constructs themselves. One of the basic concepts in structural modelling is that, although we have a set of observed measures of a theoretical construct of interest, we are not inherently interested in this set of observed measures. Instead, we are interested in the unobserved latent factor that is thought to have given rise to the set of observed measures. Similarly, within the latent curve framework we are not inherently interested in the observed repeated measures of the construct over time. Instead, we are interested in the unobserved factors (chronometric factors) that are hypothesized to underlie these repeated measures. However, unlike in the standard SEM factor model where we would like to estimate the latent factor of an independent variable, in the latent curve model we would like to estimate latent factors that represent the growth trajectories thought to have given rise to the repeated measures over time." The LGC model provides for a method for expressing the individual intercept and slope components of growth as a function of group and individual differences.

These are expressed as

$\eta_{\alpha i}$ = μ_α + $\zeta_{\alpha i}$ ………………………………….*(6.3)*

$\eta_{\beta i}$ = μ_β + $\zeta_{\beta i}$ …………………………………..*(6.4)*

..Suggesting that an individual's own intercept and slope can be expressed as an additive function of an overall mean intercept (μ_α) and mean slope (μ_β) for the entire sample plus the individual's own deviation from each of these mean values. The mean values are referred to as fixed effects and the deviation values as random effects. Now, the observed repeated measures of the latent variable have now been smoothed over to provide an estimate of the trajectories thought to underlie the repeated measures. The variance of the deviation terms in Equations above (6.3 and 6.4) is a direct estimate of the degree of individual variability in the intercepts and slopes within the sample; the greater the variance, the greater the individual differences in starting point and rates of change over time. With the inclusion of explanatory variables, the above equations change into an equation for conditional growth model accounting for the impact of the exploratory variables on the growth trajectories and the initial levels of latent variables.

The conditional growth model can thus be expressed as:

$\eta_{\alpha i}$ = μ_α + $\gamma_1 X_I$ + ……… + $\gamma_i X_I$ + $\zeta_{\alpha i}$ ……………………….(6.5)

$\eta_{\beta i}$ = μ_β + $\gamma_1 X_I$ + ……… + $\gamma_1 X_I$ + $\zeta_{\alpha i}$ ……………………….(6.6)

Model Evaluation

We consider the following criteria for evaluating the model fit:

- The relative magnitude of the omnibus χ^2 and the associated p values (Curran 2002)

- The RMSEA - root mean squared error of approximation at 90% Confidence Interval (0.05 to 0.08 indicating a better fit, smaller values indicating a better fit). (Browne and Cudek, 1993, Preacher 2006,)
- The SRMR – Standardised root mean squared residual (Preacher 2006, Joreskog and Sorbom, 1996), which is the square root of the average squared absolute difference between observed correlation and model implied correlation – a smaller value indicates better fit).
- NNFI –The non-normed fit index (Bentler and Bonnet, 1980, Tucker and Lewis, 1973). The NFI has been demonstrated to be robust to violations of distributional assumptions.

Development of the Latent Growth Curve (LGC) Model

The questions that we are addressing with the development of the LGC model are as follows:

1. Model the growth (change) in the buying behaviour, as measured by the order value and the number of orders, over a period of 1 year.
2. The factors that impact the initial level and the rate of change of the buying behaviour
3. The impact of the habit score on behavioural change.

We begin our analysis by studying the impact of time, considering an unconditional latent growth model. Since our objective here is to understand the impact of various variables on the growth of the number of orders and the growth in the value of purchases, as an indicator of behavioural loyalty, we select only that subset of customers where we have all the values of the identified independent variables available in the dataset. We hence have about 1200 customers over a period of 12 months from January 2014 to December 2014. This is the year where we had a complete set of observations of the advertising and complaints variable. Based on the recommendations of Collins (2006) and Jackson (2010), we only considered customers where there is a minimum of four observations (four orders) during the period of the analysis. In order to meet this requirement, we had to drop the age and gender variables. On inclusion of these two variables, the sample data meeting the requirements of Collins and Jackson was reduced to 118 records and building a model from such a small sample led to the model fit indices being very poor.

The final data set included 1159 customers. According to Preacher (2008), a Latent Growth Curve Model may not be able to effectively fit a parsimonious model for greater than 6 observations. In order to factor this, we also aggregated the data at a quarterly level along with a monthly aggregation.

We would like to mention once again that the except for the pin code of the delivery location, order value, the method of payment used, the voucher usage, the other independent variables such as the demographic variables were not available with the retailer for many customers since these are variables that are not mandatorily captured by the retailer or entered by the customer.

For our unconditional model, considering the impact of time on the growth of the number of orders per month for each customer, we found the χ^2 = 742.186 at p < 0.001, RMSEA = 0.13, CI_{90} = (0.122, 0.139), p (RMSEA < 0.05) = 0.001. The Standard Root Mean Squared Error (SRMR) is 0.11, The Comparative Fit Index (CFI) is 0.844 and Tucker Lewis Index (TLI) is 0.898.

The mean estimates of the intercepts were $\mu\hat{}_{\alpha}$ = 1.484 and the slope $\mu\hat{}_{\beta}$ = =0.0808 indicating that the customers understudy had a significant initial difference in the number of orders and a linear increase of 0.0808 units per time. The variance estimates of the intercept was found to be ψ_{α} =2.060 and the slope was ψ_{β} = 0.027 indicating that there was variability, albeit small, for individual customers at the group level estimates. The covariance between the intercept and slope ($\rho\hat{}_{\alpha\beta)}$ was found to be -0.117.

The model fit indices indicate that the model does not have a very good fit. .

We next include the explanatory variables to understand the impact of these on the latent variable, to further understand the variability that we noticed in the individual intercepts and slopes.

The variable that we now consider are:

1. Spending Relative to the length of the customer relationship (Spendrel)
2. Average Order Value(aov)
3. Number of complaints raised (compl)
4. Percentage of order value paid through vouchers (voch)
5. Mode of payment (paym)
6. Std.deviation of interpurchase time (stdinter)

The slope and the intercept equations are modified accordingly as follows:

$\eta_{\alpha i} = \mu_\alpha + \gamma_1 voch_i + \gamma_2 spendrel_i + \gamma_3 Aov_i + \gamma_4 compl_i + \gamma_5 paym_i + \gamma_6 stdinter_i + \zeta_{\alpha i}$ ………………………… *(6.7)*

$\eta_{\beta i} = \mu_\beta + \gamma_1 voch_i + \gamma_2 spendrel_i + \gamma_3 Aov_i + \gamma_4 compl_i + \gamma_5 paym_i + \gamma_6 stdinter_i + \zeta_{\beta i}$ …………………………. *(6.8)*

The model estimates and fit parameters are given below:

The χ^2 = 682.59 at p=0.00, RMSEA = 0.042 CI_{90} = 0.038, 0.045, p (RMSEA < 0.05) = 0.000. The mean estimates of the intercepts were $\mu\hat{}_\alpha$ = 0.034 and the slope $\mu\hat{}_\beta$ =- 0.032 indicating that the customers understudy had a significant initial difference in the number of orders and a significant linear increase of 0.045 units per time. The variance estimates of the intercept was found to be ψ_{α} =6.210 and the slope was ψ_{β} = 0.042 indicating that there was variability for individual customers at the group level estimates. The covariance between the intercept and slope ($\rho\hat{}_{\alpha\beta)}$ was found to be -0.077.

Model with the inclusion of Habit Score

We now include the habit scores as generated earlier into the model. We found the χ^2 = 582.186 at p < 0.001, RMSEA = 0.042, CI_{90} = 0.038, 0.045, p (RMSEA < 0.05) = 0.001. The Standard Root Mean Squared Error (SRMR) is 0.02, The Comparative Fit Index (CFI) is 0.959 and Tucker Lewis Index (TLI) is 0.954.

We also aggregated the data at a quarterly level, in order to meet the recommendation of Preacher (2008), but we found the monthly model to have a better fit statistics than the quarterly model.

The regression coefficients for habit score were found to be significant at the intercept level with p = 0.000 and was found to be significant at the slope level (p=0.037). The percentage of vouchers used to pay for the order value was found to be insignificant with the initial orders and significant after the first two orders. This may be indicative of the fact that the company may have been providing un-necessary incentives for the customers for repeat purchases. All the other variables are significant at intercept level.

Discussions of the results

From the development of the habit score, we see that the time stability histogram indicates that the index is mostly concentrated around the lesser than the 50% mark, ranging from 33% to 100% suggesting that the customer orders are scattered through the month and there seems to be less stability in the time of purchase. While we see that there is a higher device stability. The stability index ranged from 40% to 100%, with the median around 70%, indicating a higher stability of the device from which the order is placed. The habit scores ranged from 0.0833 to 2.375. When we incorporated the habit scores in the LGC Model, we noticed a significant improvement in the model fit indices. We hence accept the hypothesis that the behavioural loyalty in online customers is driven by the presence of habit.

Implications, Limitations and Scope for future work

The presence of habit as an important predictor of behavioural loyalty is a very important factor for the marketer. While our study focussed on establishing the presence of habit, the marketer would need to work on policies and promotions to induce the habit. Our study also gives important directions in this regard. We established the presence of habit. However, further work is required to understand the stage (since acquisition, since first purchase, after how many orders) does habit set in. While we have studied behavioural data, linking the behavioural analysis to attitudinal scales – by developing and surveying the very same set of customers, may better help us understand loyalty in a more holistic manner. Extendibility of our results to other low-involvement products which are amenable to repetitive purchases – Further work is needed with testing our model with products such as diapers, low-cost cosmetics need to be explored further.

Selected Bibliography

1. Anderson, R. E., & Srinivasan, S. S. (2003). E-satisfaction and e-loyalty: A contingency framework. *Psychology & marketing*, *20*(2), 123-138.

2. Schrage, M. (1999). The next step in customization. *Mc Technology Marketing Intelligence*, *8*, 20-21.
3. Huffman, C., & Kahn, B. E. (1998). Variety for sale: Mass customization or mass confusion?. *Journal of retailing*, *74*(4), 491-513.
4. Blattberg, R. C., & Deighton, J. (1996). Manage marketing by the customer equity test. *Harvard business review*, *74*(4), 136.
5. Oliver, R. L. (1999). Whence consumer loyalty?. *the Journal of Marketing*, 33-44.
6. Wood, W., & Neal, D. T. (2009). The habitual consumer. *Journal of Consumer Psychology*, *19*(4), 579-592.
7. Liu-Thompkins, Y., & Tam, L. (2013). Not all repeat customers are the same: Designing effective cross-selling promotion on the basis of attitudinal loyalty and habit. *Journal of Marketing*, *77*(5), 21-36.
8. Curran, P. J., & Hussong, A. M. (2002). Structural equation modeling of repeated measures data: Latent curve analysis.