

An Analysis into the Ostensible Emotional Preamble Fairly Visible in Allegiance to the E-Commerce Brands in India

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ABSTRACT

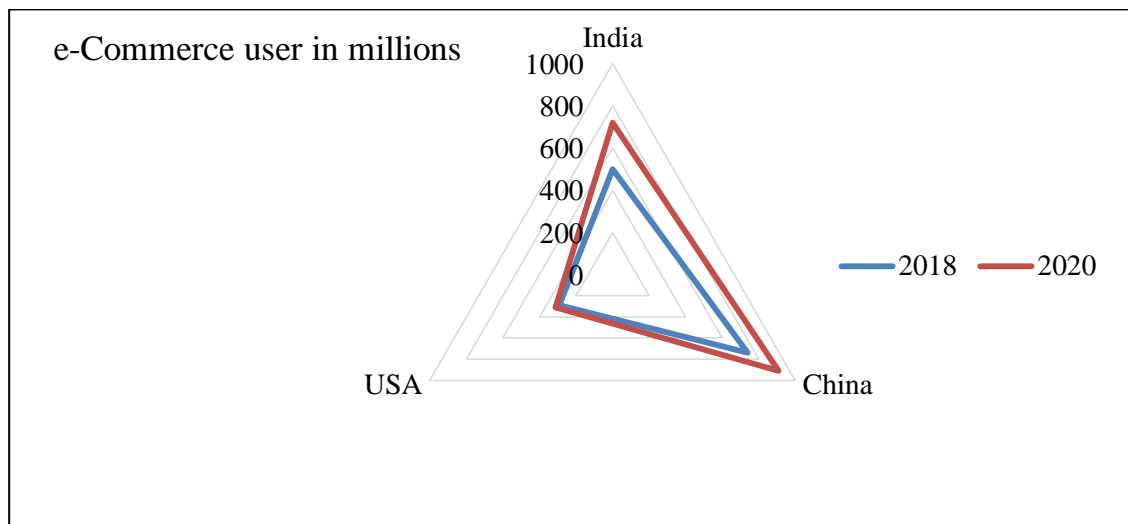
Indian e-commerce market is relentlessly buoyant with extensive adoption and abundant loyalty increasing the gross merchandise value which the consumers reflect and endorse the market players during the past three years is looked upon as a brand subservience rather the offer striking outlook. During such premonition bundled sale bonanza offered by the top market players it could be relatively evident that consistent and unperturbed manner in which such extravaganza is adopted and the mind boggling varieties are picked by the so called novice consumer in our country is worth explorable. This research paper attempts to consider those underlying assumptions behind such prolific adoptions and how the digital firms perceive and productively top up such scales in an elaborate manner. Every time it reveals the diversity and increased maturity in which consumers reinforce their learning to hunt for the better of the best choices and such phenomenon has come to stay in this market in an unobtrusive manner.

Keywords: digital metrics, adoption, learning analytics, discriminatory analysis, dominant behaviour.

INTRODUCTION:

In 2017 India with an online population of 500 million has one of the fastest growing internet populations in the world (Refer fig 1.1). A compound annual growth rate (CAGR) of 14 percent will take the total number of online users to 720 million, close to where China e-commerce market is at present. The CAGR of the Indian online user growth is nearly four times that of global rate surging due to large developments in communication technology and data consumption. The Indian e-commerce has seen a steady growth over the years since 2014 and is currently pegged at whopping US\$53 billion. Mobile data usage in India had jumped to 144 per cent (y-o-y) to 2,360 petabytes, with average consumption per user in 4G broadband reaching 11 gigabyte per month in December 2017, says a Nokia Mbit 2018 report 4G usage reaching 11 GB per user per month on average. Video content contributed up to 65 per cent of total mobile data traffic. On average, an Indian subscriber consumed 7.4 GB of data per user per month on their mobile devices over mobile networks alone, placing India ahead of developed markets like the UK, South Korea and France The average consumption over both Wi-Fi and mobile networks in India was 8.8 GB data per user per month, at par with other developed markets With a steady growth rate of little above 25 per cent, the Indian e-commerce industry is likely to cross the US\$100 billion mark by 2020. Sectors which have grown to a good market size with decent online penetration like OTAs, Online ticketing (event), Food delivery and Cabs. Emerging: These are the new upcoming sectors which have low market size very low online penetration but are growing at a much faster rate than others for instance Hyperlocal and Medicine delivery. When seeing the Organicside sectors which have gained good online penetration and have achieved a good market size and hence further growth in these can happen only organically matrimonial and Real estate classifieds coming under C2C segments.

Fig1.1: E-Commerce users projected growth 2018 to 2020



LITERATURE REVIEW:

Accordingly, this paper aims to examine the underlying concepts of Indian e-commerce buyer behaviour, including those derived from traditional consumer behavior models in the shopping field among the top players. Beginning of the digital era were e-shoppers tended to be concerned mainly with functional and utilitarian considerations. (Brown et al., 2003) On the other hand shoppers as typical “innovators” (Donthu and Garcia, 1999, Siu and Cheng, 2001), reflected to be more educated (Li et al, 1999), possessing relatively higher socio-economic status (Tan, 1999), invariably the resulting profiling part seemingly much younger than average and more likely to be male (Korgaonkar and Wolin, 1999). This led to the insight that the online consumer tended to differ from the typical traditional shopper mode and behaving in a dissimilar manner which really happening in the same iota even now. Especially in markets like India which saw a tremendous upheaval during the last 20 years to be precise. The dissimilar nature could be due to the clutter of information and social media inputs simultaneously affecting the stimuli in the information search stages. Contrary to the expectations Jayewardene et al. (2007) found that consumer purchase orientations in both the traditional world and on the Internet have narrowed down looking largely similar, and there is a indisputable evidence for the importance of social interactions (Parsons, 2002, Rohm and Swaminathan, 2004) happening due to social networking platforms wielding largely and pure recreational motives (Rohm and Swaminathan, 2004), as vividly demonstrated by virtual ethnography aka webnography termed as of “Web 2.0/3.0” blogs, social networking sites and electronic word of mouth (Wright, 2008).

The study of online consumer behaviour is gaining popularity due to the proliferation of innumerable online shopping options (Dennis et al., 2004; Harris and Dennis, 2008; Jarvenpaa and Todd, 1997). Present day in depth consumer-oriented research has examined asymmetrical psychological characteristics (Hoffman and Novak, 1996, Lynch and Beck, 2001, Novak et al., 2000, Wolfinbarger and Gilly, 2002, Xia, 2002), also demographics (Brown et al., 2003, Korgaonkar and Wolin, 1999), tradeoff leveraged perceptions of risks and end benefits (Bhatnagar and Ghose, 2004, Huang et al., 2004, Kolsaker et al., 2004), shopping motivation basically the intention to buy (Childers et al., 2001, Johnson et al., 2007; Wolfinbarger and Gilly, 2002), and shopping orientation (Jayawardhena et al., 2007; Swaminathan et al., 1999) could be reinforced on past purchases induced learning may be in the consumer electronics and consumer durables category. The technology approach has examined technical specifications of an online store (Zhou et al., 2007), including interface, design and navigation (Zhang and Von Dran, 2002), payment (Torksadeth and Dhillon, 2002; Liao and Cheung, 2002); information (Palmer, 2002; McKinney et al., 2002), intention to use (Chen and Hitt, 2002), and ease of use (Devaraj et al., 2002; Stern and Stafford, 2006). The two perspectives do not contradict each other but there remains a scarcity of published research that combines both. This is particularly relevant because it is the traditional retailers with strong images that have long been making the running in e-retail (IMRG/Capgemini, 2008; Kimber, 2001). According to Kimber (2001), shopper loyalty in-store and online are linked.

RESEARCH METHODOLOGY:

The research gap was identified that the emerging online buyer behavior and categories of varied responses make it a challenging situation for marketers and researchers to make it a point to throw more light on these phenomenon on a continual basis. India as a country aka a knowledge economy has to make itself to be the cornerstone of biggest emerging global data consumption nation supported by the advancement s in digital and technological upheaval after the post liberalization era. Mobile communication became the leading driver of disruption in which buyer becoming networked, connected making companies to leverage this new lifestyle in a mutually benefitting manner in driving content and reaping satisfaction at retention at large. Indian buying community by and large is cost conscious in a shoestring budget with rudimentary knowledge acquisition and sharing capabilities has evolved into massive digital communities since 2009 when the real ecommerce started building its strength.

Making this as the basis this study is exploratory in nature trying to fit the behavioral aspects of online buyer profile and the taste and preferences woven into the budgetary restriction as seen above. There were 342 respondents studied on a convenience sampling taken across tier I, tier II cities comprising of mixed demographic profiles ensuring their digital expertise and the e-savvy nature on purchasing and sharing opinions for more than 2-3 years. The economic prowess is also considered to give a solid push to the graduating nature of buyers from offline to mostly online only modes either squeezed of time or cost in a tradeoff manner. The survey method supported by in depth telephonic/mail based conversations were engaged.

STATISTICAL ANALYSIS AND INTERPRETATION:

To analyse the collected data two major statistical tools were attempted.

Exploratory Factor Analysis:

Factor analysis was performed to assess the construct validity for each item of the measurement scale (Bagozzi & Edwards, 1998; Hair, Anderson, Tatham, & Black, 1998). It was examined through convergent validity. Convergent validity is tested by estimating factor loading, and the values should be greater than 0.50. Reliability of the items was assessed by examining internal consistency through Cronbach’s alpha (α) method. For the reliability of the scale, the value of alpha (α) should be greater than 0.70 (Nunnally, 1978). As is evident from the Table 2, the factor loading of the entire multi-item scale is greater than 0.50, which ranges from .567 to .879. The reliability of each construct exceeds the value 0.70. Overall, the data is supported for reliability and comparable factor structure of three multi items scale, which allows a meaningful study of relationships with constructs. The strength of correlation is denoted by r, which is also called the coefficient of correlation. On the other hand, regression analysis is a statistical procedure for analyzing an associative relationship between a metric dependent variable and one or more independent variables (Malhotra & Dash, 2010).

Table 1.1: Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	4.179	46.436	46.436	4.179	46.436	46.436	4.033	44.810	44.810
2	2.491	27.675	74.112	2.491	27.675	74.112	2.637	29.302	74.112
3	.641	7.123	81.234						
4	.519	5.772	87.006						
5	.318	3.530	90.536						
6	.302	3.358	93.894						
7	.239	2.657	96.551						
8	.182	2.020	98.572						
9	.129	1.428	100.000						

Extraction Method: Principal Component Analysis.

Table 1.2: Rotated Component Matrix^a

	Component	
	1	2
TimeofSale	.758	.012
NewLaunches	-.121	.847
Attractive Discounts	.321	.791
Reliability	.267	.760
Payment Options	-.154	.830
Fast Delivery	.904	.020
Returnable	.921	.018
BRAND	.891	.099
LOOKandFEEL	.887	.132

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 3 iterations.

Table 1.3: Component Extraction

Components	% of Variance	Variable included in the factor	Loading
1	44.810	TimeofSale	.758
		Fast Delivery	.904
		Returnable	.921
		BRAND	.891
		LOOKandFEEL	.887
2	29.302	NewLaunches	.847
		Attractive Discounts	.791
		Reliability	.760
		Payment Options	.830

Inference:

The above table 1.3 shows the Component extraction, which was prepared on the basis of rotated component matrix (shown in table 1.2). The table 1.2 shows the two components 1 and 2 which had Eigen Values more than 1 in factor analysis done. Each Component constitutes of items which have Eigen value more than 0.5 in the Rotated Component matrix table 1.2. The Components are in order of percentage of variance explained by the collective items taken together.

It is observed that the factors like TimeofSale, Fast Delivery,Returnable,BRAND and LOOKandFEEL are the most important factors considered by the respondents while preferring the portal . Whereas factors like NewLaunches,Attractive Discounts,Reliability,Payment Options are on the contrary the least important factor considered while choosing a ecommerce portal.

Discriminant Analysis:

Summary of Canonical Discriminant Functions:

Eigenvalues				
Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	1.081 ^a	77.1	77.1	.721
2	.321 ^a	22.9	100.0	.493

a. First 2 canonical discriminant functions were used in the analysis.

Function 1: Attractive discounts

Function 2: Attractive discounts and Time of sale

The Eigen value gives the proportion of variance explained. A larger Eigenvalue explains a strong function. The canonical relation is a correlation between the discriminant scores and the levels of these dependent variables. The higher the correlations value, the better the function that discriminates the values. 1 is considered as perfect. Here, we have the correlation of 0.721 is comparatively high.

Testing hypothesis regarding discriminating power of the variables:

Null Hypothesis H₀: There is no significant discriminating power in the variables.

Alternate Hypothesis H₁: There may be a significant discriminating power in the variables.

Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1 through 2	.364	242.552	6	.000
2	.757	66.723	2	.000

Here $0.000 < 0.05$, therefore we reject null Hypothesis H₀ and accept alternate Hypothesis H₁ and conclude that based on the sample data, there may be a statistically significant discriminating power in the variables included in the model. Hence, we can proceed to develop the Discriminant Equation. The test of the functions as mentioned earlier is the test with the null hypothesis. The Wilks Lambda is one of the multivariate statistics calculated by SPSS. The lower the value of Wilks' Lambda, the better. In the present case the value is 0.364. The Chi-square is 242.552 with 6 degree of freedom, which is based on the groups present in the categorical variables. A Wilks Lambda of 1.00 is when the observed group means are equal, while a small Wilks Lambda is small when the within-groups variability is small compared to the total variability. This indicates that the group means appear to differ. we are rejecting the Null Hypothesis H₀ and accepting the alternate hypothesis H₁ and proceeding further with the Discriminant Analysis.

Standardized Canonical Discriminant Function Coefficients

	Function	
	1	2
TimeofSale	.379	.926
AttractiveDiscount	-.831	.213
TopBrands	.517	-.291

The standardized canonical discriminant function coefficient is used to calculate the discriminant score. The score is calculated as a predicted value from the linear regression using the above standardized coefficients and the standardised variables. Based on the coefficient above we can rank the relative important predictor variables as summarized below: -

Ranking of the Variables:

Predictor Variable

Rank	Attractive Discounts	Attractive Discounts and Time of Sale
1	Top Brands	Time of Sale
2	Time of Sale	Attractive Discounts
3	Attractive Discounts	Top Brands

Canonical Discriminant Function Coefficients

	Function	
	1	2
TimeofSale	.092	.225
AttractiveDiscount	-.194	.050
TopBrands	.155	-.087
(Constant)	.937	-3.623
Unstandardized coefficients		

Inference: Since the predictive equation is being constructed, the unstandardised canonical coefficient will be used to construct the discriminant function as follows: -

$$Z = 0.937 + 0.092(\text{TimeofSale}) - 0.194(\text{AttractiveDiscount}) + 0.155(\text{TopBrands})$$

Thus the Canonical Discriminant Function Coefficient indicates the unstandardised scores of the independent variables.

CONCLUSION:

Indian e-consumer is gearing up for an innocuous transformation and ready with all the tools techniques more importantly the necessary data to equip them to fulfill their gratification in more than the equitable proportions. Citing this our online forms started vibrantly tapping into this open commerce marketing ecosystem and using technology and data analytics to help shoppers find their wishful products of their own design and choice and the need along with the additional factors such as e-wallets, faster net banking facilities started playing a significant role behind consumer's changing buying behaviour. Consumers today are realizing the intrinsic benefits of digitization and increasingly becoming insatiable demanding for more personalised preferences and unique ways and means of satisfying their innate desires. We can easily observe that consumers in large metros say Tier-I cities are opting for online retail and e-commerce for most of their purchases and the trend is slowly percolating as well as in non-metro cities or Tier II as well. It won't be a great surprise with the significant increase of internet penetration and mobile telephony supported by smartphones and jification of cheapest data across metros and non-metros, shopping online on app based interfaces are becoming a digital age trend in the Indian market and according to a recent survey by Criteo, the performance marketing Technology Company, about 74 per cent of Indian participants in the survey stated they have installed two to five retail and shopping apps on their smartphones. It is distinctly seen that Indian e-consumers are getting more and more familiarized and abundantly comfortable about online shopping due to the discussed parameters easy payment options, return policies and faster delivery time and various types of discounts which attract consumers like amazon prime and other preferred and preferential categories extended to the buying community. The interactive websites, easy navigating and finalizing options making the necessity for literacy not a serious variable. By comfortably interacting with easy interfaces and repetitive experimenting with features the online buyer is becoming of age.

REFERENCES:

- Agarwal, R., Sambamurthy, V. and Stair, R. (2000). Research report: the evolving relationship between general and specific computer self-efficacy – an empirical assessment, *Information System Research*, Vol. 11 No. 4, pp. 418-30
- Ajzen, I. (1991). The theory of planned behaviour, *Organisational Behaviours and Human Decision Processes*, Vol. 50, pp. 179-211
- Bruyn, A. & Lilien, G.L. (2008). A multi-stage model of word of mouth through viral marketing, *International Journal of Research in Marketing*, 25 (3), 143-225.
- Jayendra Sinha and Jiyeon Kim (2012). Factors affecting Indian consumers' online buying behavior. *Innovative Marketing*, 8(2)
- Bailay, Rasul (2003). In India, shopping takes on a whole new meaning, *Wall Street Journal (Eastern edition)*, December 16, p. A. 15.
- Beilock, Richard and Dimitrova, Daniela V. (2003). An Exploratory Model of Inter-country Internet Diffusion. *Telecommunications Policy*, 27 (3-4), pp. 237-252.
- Hubacek, Klaus, Guan, Dabo & Barua, Anamika (2007). Changing lifestyles and consumption patterns in Developing countries – A scenario analysis for China and India, *Futures*, 39 (10), pp. 1084-1096.
- Kumar, Archana, Lee, Hyun J. & Youn, K. Kim (2008). Indian consumers' purchase intention toward a United States versus local brand, *Journal of Business Research*, 62 (5), pp. 521-527.
- Srivastava, R.K. (2008). Changing retail scene in India, *International Journal of Retail and Distribution Management*, 36 (9), pp. 714-721.
- Tuaber, Edward M. (1995). Why do people shop? *Marketing Management*, 42, pp. 58-60.
- Venkatesh, Viswanath & Davis, Fred D. (2000). A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies, *Management Science*, 46 (2), pp. 186-204.
- Vijaysarathi, Leo R. & Jones, Joseph M. (2000). Intentions to Shop using Internet Catalogues: Exploring the Effects of Product Types, Shopping Orientations, and Attitudes towards Computers, *Electronic Markets*, 10 (1), pp. 29-38.
