Examining Internet Behavior of Young Technology-Literate Consumers in India

Completed Research

Dr. Narasimha Rao Vajjhala  
School of IT & Computing  
American University of Nigeria, Nigeria  
narasimha.vajjhala@aun.edu.ng

Prof. Kenneth David Strang  
School of Business & Economics  
State University of New York, USA  
kenneth.strang@plattsburgh.edu

Abstract

In this study, we analyzed consumer Internet behavior in India since there were several unique cultural dimensions of interest. After reviewing the literature, we tested hypotheses that demographic and psychological factors such as happiness, excitement, satisfaction, positive feelings, pleasant feelings, gender, age, and income level could predict consumer Internet purchase behavior. We used Spearman correlation, binary logistic regression, and discriminant analysis techniques, which resulted in effect sizes ranging from 9.5% to 59.5%. Spearman correlation confirmed that gender, age, and income level were related to consumer Internet purchase behavior. Several binary logistic regression models with goodness-of-fit-tests revealed that all satisfaction, happiness, positive feelings and pleasant feelings, but not excitement, could predict consumer Internet purchase intention. A Discriminant Analysis model was able to correctly classify 87.3% of the sample respondents using two factors, and a second model with only one factor correctly categorized 90.5% of the consumers as willing to purchase on the Internet.

Keywords

Consumer, Internet, behavior, risk-avoidance, culture, power, regression, purchase.

Introduction

There has been a dramatic increase in consumer shopping on the Internet in India (Nittala 2015). At 1.32 billion, India has the second largest population in the world after China although the Internet penetration is quite low (Khare 2016). India has the second largest internet user base in the World with 350 million users in 2015 that increased to 503 million users in 2017 (Agarwal and Dixit 2017). Nonetheless, the annual growth rate of the Internet users is high at 41%, and Internet sales are projected to reach $75 billion (Khare 2016). However, only 13.25% of these internet users shopped online in 2013, and this was expected to increase to around 28% by the end of 2017 (Agarwal and Dixit 2017). Hence, there is significant scope for growth in Indian e-commerce consumer base. Furthermore, India is undergoing an unprecedented economic boom followed by a substantial increase in consumer spending (Nittala 2015). According to Thamizhvanan and Xavier (2013), firms need to understand the preferences and mindset of Indian online users apart from other factors, such as the government policies and industry developments. This makes India attractive to study.

Indian consumer behavior on the Internet may be difficult to conceptually model. First, Internet use in India is largely driven by the young generation as evidenced by 75% of the Internet users being in the 25-35 age range (Khare 2016). Second, the culture in India is uniquely different than any other country because there is a high acceptance of power such as government control combined with a low level of risk avoidance characterized by acceptance for the unexpected and a philosophy to create innovative ‘adjustments’ to bypass rules (Insights 2017; Strang and Vajjhala 2017). Cultural factors can significantly influence the buying decisions of individuals. Since India has a different cultural profile as compared to other Western countries, in particular, the e-commerce marketing strategies that have worked in western cultures may not be successfully replicated in the Indian market. Indian culture is strongly impacted by Hinduism and Buddhism religious beliefs grounded in Karma life after death, but paradoxically global
terrorism has taken more lives than in any other country (Strang 2018a). Corruption has also negatively impacted India (along with many other countries). Recently Prime Minister Narendra Modi eliminated 500 and 1000 rupee notes to reduce tax evasion and impair the black market economy (Bremmer 2017). After the elimination of these currency notes, the Indian government is leading a push towards cashless transactions and the use of online payment systems. Modi also recently initiated a biometric identification system to combat corruption and fraud (Bremmer 2017) which may impact Indian consumer culture towards Internet behavior.

In addition to India being an important country in the new e-commerce-driven global marketplace, as well as having a complex national culture, another reason for studying consumer Internet behavior is there is not enough scholarly literature. One problem is that most of the studies were conducted in Western countries like the USA and their trading partners (Hur, Kang and Kim 2015). Online consumer behavior studies conducted primarily in Western countries cannot be generalized to other cultures, such as Asian or in particular to Indian cultures where there is a rising young generation of Internet users (Strang 2018b). For instance, several of the factors that were found to be significant in explaining online consumer behavior in Western countries were not relevant in Thailand and India samples (Nittala 2015).

In this study, the literature was reviewed to identify the most relevant factors, theories, and models that researchers have used to understand consumer purchasing behavior on the Internet. The main factors identified from the literature tested in the unit of analysis in this study were: the extended emotion of trust (Plutchik 1997) and online consumer behavior (Strang 2018b). Our goal was to leverage those mainstream theories to explain the Internet behavior of the emerging young generation of consumers in India. The purpose was to be able to generalize our findings to India as well as other countries, given the global online economy that we now have. In the introduction, we examined the purpose and the importance of studying the Internet consumer behavior in India. In the next section, the existing literature about consumer Internet behavior and culture is reviewed.

**Literature Review**

*Importance of studying consumer Internet behavior and culture*

E-commerce refers to any commercial transaction conducted over a computer network, such as the Internet (Huseynov and Yildirim 2015). Online shopping was identified as one of the fastest growing Internet activities for several reasons including convenience, the increasing penetration of smart devices, easy price comparisons, and the availability of a wide variety of products. Business to consumer (B2C) e-commerce sales is likely to reach around 2.5 trillion dollars by 2018 (Huseynov and Yildirim 2015). There has been an exponential growth in Internet usage, with the number of users reaching 3.58 billion in 2017, as compared to less than 1 million in 1990 (Mazaheri et al. 2014). At 1.32 billion, India has the second largest population in the world next to China, and with 100 million Internet users growing at a yearly rate of 41%, coupled with Internet sales revenue nearing $75 billion, it is indeed essential to study consumer behavior in India (Khare 2016). Furthermore, India is undergoing an unprecedented economic boom followed by a significant increase in consumer spending (Nittala 2015) and much of that spending will likely take place using e-commerce over the Internet.

India is one of the fastest growing highly educated English-speaking economies of the world, and it has witnessed an unprecedented economic boom we well as a significant rise in consumer spending over recent years (Nittala 2015). India offers an enormous opportunity for online marketers trying to understand the behavior of online consumers. Online consumer spending was $30 billion in 2015, and it is likely to rise significantly as the number of Internet users is expected to triple from the current number of around 125 million users. With a population of 1.32 billion, India is one of the most significant frontiers for online marketers. In comparison, the number of Internet users is around 80% of the population in the United States, whereas in India the percentage is just over 10%. This shows that there is likely to be a significant influx of online consumers in India over the next few years. Thus, there is a unique opportunity to design e-commerce systems for India consumers at the early adoption stage.

According to Yoon (2009), e-commerce has an international scope so national culture can have an impact on the behavior of the consumers. Yoon (2009) in his study of effects of national cultural dimensions on consumer’s acceptance of e-commerce found that power distance and individualism did not have a
significant impact but uncertainty avoidance and long-term orientation had a moderating effect on the consumer behavior. According to Insights (2017), India ranks high in power distance index (PDI) at 77, indicating a preference for hierarchy in society and organizations. India has a moderate level of individualism (IDV) at 48, meaning that Indian culture has both collectivistic and individualistic traits. India is considered a masculine society instead of a feminine orientation with a nominally high value of Masculinity (MAS) at 56 (Insights 2017). India has a medium-low value for uncertainty avoidance (UAI) at 40, which demonstrates that people accept the unknown and are willing to take risks including adjusting the rules when necessary. This indicates that the risk-taking propensity is relatively higher in India as compared to several other countries. It is not surprising considering that trust is a significant factor in online shopping, so a higher risk-taking propensity is indicative of marginal levels of trust in the Internet.

Similarly, the long-time orientation (LTO) value for India is also intermediate, with a score of 51, as the time dimension is not linear as in Western countries. India scores quite low in the indulgence dimension (IND), with a score of 26, indicating a culture of restraint with a tendency to cynicism and pessimism (Insights 2017). However, since these cultural dimensions are national in scope, it would be irrelevant to test them within a sample drawn from India. Instead, knowing the national cultural dimensions of India consumers helps us to rationalize the behavior once we have tested other factors. In particular, knowing national cultural dimensions would assist in understanding how to generalize the findings to other countries with similar values. Additionally, knowing the national cultural values would be useful to facilitate comparative studies on consumer Internet behavior in other countries.

**Factors and Models for Studying Consumer Internet Behavior**

A review of the literature indicated that two broad approaches were being used to empirically examine consumer Internet behavior: Psychological and technical. The consumer psychological approach for studying Internet behavior has focused on examining culture factors, demographics, shopping motivation and personality orientation (Dennis et al. 2009; Zhou et al. 2007). The technology approach for examining consumer Internet behavior has focused on technical specifications of the website, payment, user intention and ease of use (Dennis et al. 2009; Zhou et al. 2007). However, the emergence of mobile technology such as smart phones has put more emphasis on consumer behavior factors such as motivation, personality, motivation and culture. Therefore, it would be relevant to review literature in the psychological category.

Several key psychological consumer behavior models were developed and used by researchers over the years, notably the Theory of Reasoned Action (TRA) model (Ajzen and Fishbein 1980), Engel Kollet Blackwell (EKB) model, Motivation-Need Theory, and Hawkins Stern Impulse Buying (Zhou et al. 2007). Most consumer behavior scholars have used some of these models or expanded on them to develop consumer Internet behavior models. The Theory of Planned Behavior (TPB), the Innovation Adoption and Diffusion Model, Social Exchange Theory, Attribution Theory, and Balance Theory have also been applied to understand consumer trust and online decision making behavior (Hwang and Jeong 2016). Several studies have explored the Stimulus-Organism-Response (SOR) framework (Mehrabian and Russell 1974) to measure the influence of website atmospherics on consumer Internet purchasing behavior (Mazaheri et al. 2014). Most of these models do not measure consumer behavior in an online purchase or planned purchase situation. Additionally, the factors from many of these models are endogenous and require complex measurement so they would be challenging for the layperson to apply for target market segmentation (Strang 2018b). Thus, in this review, we focus on specific emotional or demographic attributes that ought to be relevant for estimating young technology-literature consumer purchase behavior in India.

The common assumption of most consumer Internet behavior models is that actual behavior can theoretically be predicted by beliefs, attitudes, intentions, and emotions (Hwang and Jeong 2016). Adoption of technology by consumers depends on a variety of demographic factors, including education, income, age, sex, and access to infrastructure apart from the perception of technology reliability, including perceived usefulness, perceived ease of use, and trust (Szopiński 2016). However, numerous studies employing these models have not been significant or have not tested planned or actual behavior.

The underlying approach in most of the psychological models was to identify consumer factors related to demographics and trust in the online Internet context to predict planned buying behavior. In addition to
the factors mentioned above, gender, occupational experience, item price, item quality, and time required to purchase were found to predict consumer planned Internet buying behavior (Vacchani and Bhayani 2012). Interestingly, the price level was not a strong factor influencing consumer Internet behavior as compared to other factors, such as the reduced effort in the shopping, information about company policies, product returns, delivery time, and online assistance available. Richard et al. (2010) emphasized the importance of Web atmosphere to motivate consumer Internet behavior, including structure, the effectiveness of content, information, and entertainment. Since India has a high masculine culture (Insights 2017), it is likely that males will be more likely to make Internet purchases and therefore income levels will be higher as compared to those not trusting the Internet. Since young consumers in India are increasing more quickly as Internet users, we anticipate age to be inversely related to online behavior. Given the overwhelming evidence reviewed above that specific demographics factors can explain consumer Internet purchasing behavior, and since our study is focused on understanding the socio-economic and cultural drivers of Indian consumers, we intended to test the following hypotheses:

H1a: Male gender will be positively related to consumer Internet behavior in India (males more active);

H1b: Age will be negatively related to consumer Internet behavior in India (younger people more active);

H1c: Income level will be positively related to consumer Internet behavior in India (richer people more active).

We recognize other demographic factors could impact Indian consumer Internet behavior, such as occupation and education, so we will collect data and report descriptive statistics rather than form hypotheses to test for broad nominal categories with potential empty classification cells.

Vacchani and Bhayani (2012) also identified several other relevant factors, including price, service quality, delivery assurance, trust in vendors, customer support, privacy, ease of use, and personalization. Some of the studies exploring factors that impede consumers in making online purchases have identified factors, such as demographic characteristics, consumer lifestyles, and personal innovativeness (Hwang and Jeong 2016). Huseynov and Yildirim (2015) identified two types of online consumer shopping motivation, namely utilitarian and hedonic. Utilitarian shopping motivation is defined as goal-oriented and mission-critical, as compared to hedonic motivation behavior, which was characterized by a focus on enjoyment, satisfaction, and happiness. Moon et al. (2008) defined personalization as the customization of some of the features of a product so that the customer feels happy and can identify with the product or service. Both these behaviors had positive associations with customer satisfaction and purchasing intention. These studies suggest that motivation can predict consumer behavior (Huseynov and Yildirim 2015). Therefore we developed the following predictive motivation hypotheses to test this:

H2a: Consumer satisfaction (happy) will predict purchasing intention;

H2b: Consumer satisfaction (satisfied) will predict purchasing intention.

These two hypotheses are intended to show support for what findings reviewed above in the literature and also they support the common sense deduction that happy online consumers will highly motivated to plan to purchase and to actually follow through on an intended purchase.

Three situational descriptors of emotions, namely, pleasure, arousal, and dominance, can describe the emotive responses of an individual to the environmental stimuli (Mehrabian and Russell 1974). The pleasure indicator in the context of online consumer behavior is reflected by the website likeability, while arousal, referring to the degree of stimulus that an individual feels, is indicated by the motivational power of the website (Mazaheri et al. 2014). Due to the differences in culture between India versus the Western countries where these models were tested, it is unlikely that Indian consumers will fully understand constructs like arousal and dominance in the context on consumer Internet behavior surveys. On the other hand, emotional terms such as pleasurable, exciting and positive, so we developed the following hypotheses to test these emotive and motivational factors:

H3a: Consumer excitement (not calm) will predict purchasing intention;

H3b: Consumer positive feelings (not negative) will predict purchasing intention;

H3c: Consumer pleasant feelings (not unpleasant) will predict purchasing intention.
Numerous marketing studies point out that excitement can impact planned behavior. Plutchik (1997) argued that many psychological tests of planned behavior involve extended emotions namely trust and expectation of a positive or pleasant results. Given these findings in the literature, and knowing we were examining planned Internet consumer behavior but without a priori knowledge of previous purchases, we wanted to test excitement, and positive versus negative attitude towards an Internet purchase. By forming separate hypotheses around these three attitudes, we can isolate the impact of each one, even though they may in fact all be correlated as would be expected given the literature reviewed above.

Vacchani and Bhayani (2012) emphasized the importance of examining critical success factors, such as ease of navigation, quick loading times, and accurate product or service delivery systems, as these directly influence customer satisfaction, contributing directly to the long-term success and survival of online businesses. However, factors such as loading times are website specific and satisfaction constructs are already captured in other factors explained earlier. Thus, although we wanted to declare these factors, we did not feel they would be relevant to test in our study since we were not using a specific website.

In the literature review, we examined the importance of studying the consumer behavior and culture. The factors and models for studying consumer internet behavior were also explored in the literature review. In the next section, the research method and design used in this study are presented followed by the discussion of the hypotheses test results.

**Method**

The research design was a within-group correlational strategy. The unit of analysis was the predictive relationship between demographic or motivational factors with planned Internet purchasing behavior of consumers in a high PDI and low UAI country, namely India. Thus, this was an individual level of analysis and not a group or country type of design. We used a survey to collect data since we desired a large sample and we could not access the relevant population through interviews or using other data collection techniques. We developed a survey and pilot tested it on students in India (revisions were made, and it was successfully retested with business people in India).

We intended to generalize our findings to consumers in India who could use the Internet, and furthermore, to be able to generalize these results to other nations with similar national culture dimensions. We selected the two southern states known to have a high concentration of Internet access: Andhra Pradesh and Telangana. These two states were chosen as they were among the top-5 states in the Gross State Domestic Product (GSDP) indicating that the affordability and availability of technology were much higher as compared to other Indian states. Andhra Pradesh and Telangana used to be one single state before the bifurcation in 2014. The state of Andhra Pradesh stood seventh regarding geographic area and 10th regarding population among the 29 Indian states. We used social media and email to identify a random sample frame of 110 participants. Data were collected from 63 participants using an online survey instrument. The participants included a diverse demographic distribution with the main criteria being they had access to the online Internet shopping and they had shopped once online.

The survey questions captured demographic characteristics (independent factors) using exact value for age and gender. The other independent factors were captured using Likert style questions (1-5, strongly disagree to strongly agree). The survey recorded planned purchase behavior (dependent variable) as a dichotomous two scale nominal data type (yes or no). Nonparametric statistical techniques, such as Chi-Square Test of Independence, Cluster Analysis, Spearman Correlation and Discriminant Analysis are appropriate for testing hypotheses of median distributions or relationships between ordinal and nominal data types as well as the predictive capability for a nominal dependent variable. The confidence level was set at 95%. Minitab version 18 was utilized for the tests and to format the results.

**Analysis and Discussion**

**Preliminary Analysis**

Table 1 summarizes the demographic characteristics of the sample. As can be seen from table 1, the majority of participants worked in managerial, education or IT related positions. However, there was a broad coverage of many types of occupations in the sample across the industries, sectors, and disciplines.
(private and public). The exception was there were no construction or natural resource occupations (e.g., agriculture or fishing). Income level was typical of the Indian population with Internet access. Most participants had a four-year bachelor or master degree which is not typical of the entire India population. The majority of participants were married, with a sizable proportion single, and a few in other marital situations. In terms of gender (not shown), 38.7% were female, and 61.3% were male. Mean age was 33.6 (SD=9.5), the coefficient of variation was 28.3% (moderate dispersion), and the median age was 31 years.

<table>
<thead>
<tr>
<th>Occupation</th>
<th>Income (Rupees)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Management</td>
<td>15.9% ₹400,000 to ₹499,999 36.5%</td>
</tr>
<tr>
<td>Education, Training, and Library</td>
<td>12.7% ₹500,000 to ₹599,999 25.4%</td>
</tr>
<tr>
<td>Computer and Mathematical</td>
<td>11.1% ₹600,000 to ₹699,999 11.1%</td>
</tr>
<tr>
<td>Business and Financial Operations</td>
<td>6.4% Less than ₹300,000 9.5%</td>
</tr>
<tr>
<td>Sales and Related</td>
<td>6.4% ₹300,000 to ₹399,999 9.5%</td>
</tr>
<tr>
<td>Production</td>
<td>6.4% Over ₹700,000 7.9%</td>
</tr>
<tr>
<td>Architecture and Engineering</td>
<td>4.8%</td>
</tr>
<tr>
<td>Legal</td>
<td>4.8%</td>
</tr>
<tr>
<td>Arts, Design, Entertainment, Sports</td>
<td>4.8% 4-year college degree 50.0%</td>
</tr>
<tr>
<td>Healthcare Support</td>
<td>4.8% Graduate-level degree 29.0%</td>
</tr>
<tr>
<td>Personal Care and Service</td>
<td>4.8% Some college, no degree 9.7%</td>
</tr>
<tr>
<td>Healthcare Practitioners and Technical</td>
<td>3.2% Doctorate or PhD 4.8%</td>
</tr>
<tr>
<td>Food Preparation and Serving Related</td>
<td>3.2% High school diploma 3.2%</td>
</tr>
<tr>
<td>Office and Administrative Support</td>
<td>3.2% 2-year college degree 3.2%</td>
</tr>
<tr>
<td>Life, Physical, and Social Science</td>
<td>1.6% Primary school 0.0%</td>
</tr>
<tr>
<td>Community and Social Service</td>
<td>1.6% Other 0.0%</td>
</tr>
<tr>
<td>Building and Grounds Cleaning</td>
<td>1.6%</td>
</tr>
<tr>
<td>Installation, Maintenance, and Repair</td>
<td>1.6% Marital Status</td>
</tr>
<tr>
<td>Transportation and Materials Moving</td>
<td>1.6% Married 58.7%</td>
</tr>
<tr>
<td>Protective Service</td>
<td>0.0% Single, never married 33.3%</td>
</tr>
<tr>
<td>Farming, Fishing, and Forestry</td>
<td>0.0% Divorced 6.4%</td>
</tr>
<tr>
<td>Construction and Extraction</td>
<td>0.0% Widowed 1.6%</td>
</tr>
</tbody>
</table>

Table 1. Demographic Descriptive Characteristics of Sample (N=63)

**Hypothesis Test Results**

We used the survey item “What is the probability that you would purchase the device in the near future?” which was a dichotomous binominal data type with the choice of “probable, likely” (1) or “improbable, unlikely” (0) as the factor to correlate with gender, age and income level.

The first hypothesis H1a that male gender was positively related to consumer Internet behavior in India was accepted. A Chi-Square Independence Test revealed that there was a significant relationship between gender and Internet purchase intention. In the sample, only 32.26% of females intended to make the Internet purchase while in contrast 51.61% makes said it was probable. The conditional probability that a participant intending to make an Internet purchase was male is 61.5% (high). The Chi-Square $X^2 (63,1)=
Examining Internet Behavior of Young Technology-Literate Consumers

0.008, \( p=.927 \) (two-sided), with a Likelihood Ratio Chi-Square \( X^2=0.008, p=.927 \) (two-sided). However, the effect size was very slight with a Cramer’s \( V^2=0.000135 \) (this was too small to support inferences).

The second hypothesis (H1b) that age was negatively related to consumer Internet behavior in India was supported. Younger participants were more likely (probably) have an Internet purchase intention. The Spearman correlation coefficient was \( \rho(63)=-0.410, p=.001 \) (two-sided). The effect size was \( r^2=0.16 \) which is a moderate amount and suitable for making generalizations in exploratory studies.

The third hypothesis (H1c) that income level was positively related to consumer Internet behavior in India was also supported. Approximately 50% of the participants intending to make Internet purchases fell into the up to $499,000 and up to $599,000 categories, but richer and poorer people were less likely to do so. The Pearson Chi-Square \( X^2(5)=4.281, p=.04 \) (two-sided), and the Likelihood Ratio Chi-Square \( X^2=5.182 \) with \( p=0.04 \) (two-sided) confirmed this. Cramer’s \( V^2 \) effect size was 0.06795 which is small at 7% but large enough to be generalizable in exploratory studies.

The next set of hypotheses concerned the predictive motivational factors. The hypothesis (H2a) that consumer happiness with the Internet environment could predict purchasing intention was accepted. First, the Spearman correlation between happy and purchase intention revealed a strong positive relationship, with a \( \rho(63)=0.621, p=.000 \) (two-sided), having an effect size of \( r^2=38.6\% \) (high for exploratory studies). Second, a simple regression confirmed that happiness with the Internet context could predict a consumer’s intention to purchase. The simple regression F-Test (DF=2, 62)=43.54, \( p=.000 \), with an effect size of \( r^2=59.2\% \) (adjusted \( r^2=57.9\% \)), which is high. However, after the next test, both factors need to be entered into the same model, along with any control variables, to obtain a more realistic result.

The other motivation hypothesis test (H2b) that consumer satisfaction with the Internet context will predict purchasing intention was also accepted. A Spearman correlation between satisfaction and purchase intention revealed a strong positive relationship, based on a \( \rho(63)=0.67, p=.000 \) (two-sided), and an effect size of \( r^2=45.9\% \) (high for exploratory studies). A simple regression confirmed that satisfaction with the Internet context predicted a consumer’s intention to purchase. The regression F-Test (DF=2, 62)=49.57, \( p=.000 \), with an effect size of \( r^2=44.8\% \) (adjusted \( r^2=43.9\% \)), which is high.

Based on the success of the above two motivational factors being able to predict consumer Internet purchasing behavior separately, a post hoc test was performed by entering them both into the same binary logistic model. The results indicated that while both motivational factors could predict consumer Internet purchasing behavior in the same model, although the independent variables were highly correlated, with variance inflation factors of ranging from 2.45 to 5.68 suggesting they were confounding one another, and there were six residual outliers. The binary logistic regression model was significant, with an overall \( X^2(2)=24.7, p=.000 \) (two-sided) but the first factor happiness was lower and not significant at \( X^2(2)=2.17, p=.14 \) while satisfaction was significant at \( X^2(2)=14.18, p=.000 \) (two-sided). Although only satisfaction was significant, the model deviance effect size was moderately large at \( r^2=42.3\% \) (adjusted \( r^2=38.90\% \)), with an Akaike Information Criterion (AIC) of 39.66 which suggests a moderately fitting model with some information loss. An interesting estimate was that the 95% confidence level odds ratio for satisfaction was 27.9099 (CI: 4.4286, 175.8919) while happiness was 3.154 (CI: 0.7842, 12.6856). This indicates that consumers in the sample who were satisfied with the Internet context were almost 28 times more likely to make a purchase as compared to unsatisfied respondents. Although lower, consumers who were happy with Internet were 3 times more likely to plan a purchase as compared to unhappy people.

Unfortunately the goodness-of-fit tests revealed though that there was not enough evidence to claim the two-factor binary logistic model adequately represented the casual hypothesis, based on a regression deviance \( X^2(60)=33.66, p=.998 \) (no difference from a null model), a Pearson \( X^2(60)=70.77, p=.161 \) (no difference), and a Hosmer-Lemeshow \( X^2=4.40, p=.036 \) (could be different than a null model). Based on these post-hoc results, a Discriminant Analysis could be performed later since it is relevant to test the ability of multiple attribute levels to classify a two-state nominal outcome of likely to purchase versus not likely to purchase. This post-hoc test would be conditional on the finding of the following hypotheses.

The next three hypothesis tests examined the emotive predictive factors. The hypothesis (H3a) to test if consumer excitement could predict Internet purchasing intention was not supported. Although a simple regression produced a statistically significant model it has a small \( F\text{-Test}(62,1)= 6.39, p=.014 \), and a small effect size of \( r^2=9.5\% \) (adjusted \( r^2=8\% \)). A binary logistic model regression revealed being excited about
the Internet did not reliably predict buying-intention, based on a small deviance $X^2(62,1)=5.33$, $p=.021$, a large AIC of 57, as confirmed by a goodness-of-fit-test deviance $X^2(61)=53.03$, $p=.756$ (not different than a null model), and a Pearson $X^2(61)=63.00$, $p=.405$ (no different than a null model).

The next emotive predictive hypothesis test (H3b) that consumer positive feelings about the Internet would predict purchasing intention was supported. A simple regression was significant with an $F$-Test$(62,1)=67.43$, $p=.000$, the coefficient was 0.6458 ($t=8.21$, $p=.000$), and the effect size was moderately large at $r^2=52.5\%$ (adjusted $r^2=51.7\%$). The binary logistic model had a large $X^2(61,1)=29.54$, $p=.000$, with a large effect size of $r^2=50.6\%$ (adjusted $r^2=48.9\%$), and an AIC of 32.82 which indicated some information loss although it was a good fitting model. The large odds ratio of 94 (95% CI: 9.8787, 894.4514) could be interpreted that consumers in the sample having a positive attitude toward the Internet are 94 times more likely to intend to make a purchase. Nonetheless, the goodness-of-fit-tests could not confirm it was a perfect model, despite a low deviance $X^2(61)=28.82$, $p=1$ (not different than a null model), and a Pearson $X^2(61)=63.00$, $p=.405$ (also not different than a null model). The goodness-of-fit-test results are likely the result of using only one predictor, so more post-hoc tests will be used.

Finally, the third emotive factor hypothesis (H3c) that a consumer having pleasant feelings about the Internet will predict purchasing intention was supported. A simple regression was significant with an $F$-Test $(62,1)=55.82$, $p=.000$, the coefficient was -0.6515 ($t=-7.47$, $p=.000$), and the effect size was moderately large at $r^2=48.2\%$ (adjusted $r^2=47.3\%$). The binary logistic model had a large $X^2(61,1)=25.2$, $p=.000$, with a large effect size of $r^2=43.5\%$ (adjusted $r^2=41.8\%$), and an AIC of 36.76 which indicated some information loss although it was a good fitting model. The large odds ratio was insignificant. Again the goodness-of-fit-tests could not confirm it was a perfect model, despite a low deviance $X^2(60)=32.76$, $p=.998$ (not different than a null model), and a Pearson $X^2(60)=62.00$, $p=.405$ (also not different than a null model).

As with the above hypothesis test result, while the single factor binary logistic model was significant, it was unlikely to be the best model, particularly since the other factors were not added yet.

At this point, the following factors could significantly predict consumer Internet purchase intention: happiness, satisfaction with Internet, positive feelings, and pleasant feelings. There were also significant correlations between gender, age and income level with Internet purchase intention. Since there is a natural before-after sequence between these demographics factors and Internet purchase intention, they would be suitable to enter into a casual model as nominal predictors, for control and informational purposes. Therefore we tested a new binary logistic regression model using happiness, satisfaction, positive and pleasant feelings along with gender, age and income as control factors. Although the overall model was valid although with a small $F$-Test$(63,11)=12.14$, $p=.000$, only two factors were significant: Happiness and satisfaction. A two-factor binary logistic model using happiness and satisfaction to predict Internet purchase intention was significant with an $F$-Test$(62,2)=27.54$, $p=.000$, although happy was barely significant with a $t$-test$=1.97$, $p=0.056$ (VIF=1.28), but satisfaction was significant with a $t$-test$=5.48$, $p=.000$ (VIF=1.28). The VIF indicates some possible mild interaction between the two factors. However the overall model had an effect size of $r^2=47.9\%$ (adjusted $r^2=46.1\%$) which is moderately large.

Given the ability of consumer happiness and satisfaction with the Internet to predict purchase intention in the sample, we executed a Discriminant Analysis with both factors to measure the effectiveness of using these two factors to classify sample participants into a likely to purchase group versus those unlikely to purchase. The results were significant with 87.3\% (55 out of 63) of the sample respondents correctly classified into the two groups of likely or unlikely to purchase. The Linear Discriminant Function for happy and unlikely to purchase was 1.716 as compared to happy and likely to purchase at 3.829, while for satisfied the coefficient was 2.746 for unlikely as contrasted with a large 10.193 for likely to purchase. This corroborates with earlier regression results and suggests satisfaction is a stronger predictor than happiness to account for a consumer being classified as willing to make an Internet purchase. Interestingly, when isolating only the likely to purchase dependent variable in the Discriminant Analysis, 90.4\% (47 out of 52) of the sample respondents were correctly classified as being willing to make an Internet purchase using happiness and satisfaction. When the model was run with only satisfaction as the predictor of Internet purchase intention, 90.5\% (57 of 63) sample respondents were correctly classified, and of those willing to purchase 94.2\% (49 of 52) were correct. This is a very high success rate.

Despite this high success rate, the sample was very small at 63 so we have to be careful in assuming this as a defacto inference for generalizing to all young technology-literature consumers in India. Thus, this
study needs to be replicated with much larger sample sizes. Additionally, it would be valuable to replicate the study to other cultures for comparison and contrast.

**Conclusion**

We analyzed consumer Internet behavior using a small sample of participants from the two southern provinces of India to predict which demographic or psychological factors could predict purchase intention. Young people in India were selected as the sample frame for several reasons. We selected India because of their large population of 110 million Internet users who were in the 25-35 age range (Khare 2016). India was also of interest due to their unique national cultural dimensions, with a high tolerance for power and low uncertainty avoidance, which means consumers are likely to be willing to adopt new technology. The findings of this study contribute to understanding the internet behavior of young technology-literate consumers in India. The conclusions of this study add to existing literature on exploring consumer's online behavior in a complex Indian culture which is significantly different from Western countries. This study will also address the literature gap as most of the similar studies have focused on Western cultures.

After reviewing the literature, we developed hypotheses that demographic and psychological factors could predict Indian consumer behavior towards purchasing on the Internet. All but one of the hypotheses was supported (excitement was rejected). Happiness, satisfaction, positive feelings and pleasant feelings about the Internet along with gender, age, and income level were found to be statistically significant predictors of consumer purchase intention behavior, using Spearman correlation and binary logistic regression techniques. Effect sizes ranged from 9.5% to 59.5% (low to high considering it was an exploratory study). A multiple binary logistic regression with goodness-of-fit-tests revealed that only satisfaction and happiness were reliable predictors on consumer Internet purchase intention.

We executed a Discriminant Analysis with both factors, and then with only consumer Internet satisfaction to measure the effectiveness of using these two factors to classify sample participants into a likely versus unlikely to purchase group. In the two-factor discriminant analysis function model, the results were significant with 87.3% of the sample respondents correctly classified into the two groups of likely or unlikely to purchase. When satisfaction was used as the predictor of Internet purchase intention in Discriminant Analysis, 90.5% of the sample respondents were correctly classified and of those willing to purchase 94.2% were correct. This is a high success rate for a Discriminant Analysis model.

Given that the sample participants mean age was 33.6 (SD=9.5, median=31 years), and considering occupations were widely spread with a 38.7% female, and 61.3% were male split, the findings will be generalizable to the upcoming generation of young consumers in India. This brings us to the major limitation of this study, being that there was a small sample size of N=63, so we recommend this be replicated again in India. The study is also limited by the honesty of the participants' responses during the survey and the amount of time available to conduct the study.

**REFERENCES**


