

## Demographic and Interactional Predictors of Online Shopping Behavior: A Two-Way ANOVA Analysis in NCR

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### Abstract

This study examines the demographic and interactional predictors that shape the frequency of online shopping among consumers in the National Capital Region (NCR) of India. Using a structured questionnaire and a sample of 542 respondents, the research applied Pearson correlation, One-Way ANOVA, and Two-Way ANOVA to evaluate the influence of delivery time, payment terms, education, income, age, advertisement exposure, and social media activity on digital shopping behavior. Findings indicate that education and income, as standalone variables, do not significantly affect online shopping frequency, challenging traditional assumptions about socioeconomic determinants. However, a significant interaction effect between age and income was identified, suggesting that income's influence varies by generational cohort. Other interactional variables, such as education  $\times$  income and social media  $\times$  advertisement exposure, were not statistically significant. Delivery time had a weak but significant correlation with shopping frequency, while payment terms did not show a meaningful association. The results highlight the declining predictive power of static demographics and emphasize the need for behavioral and intersectional segmentation in digital commerce strategies.

**Keywords:** Online Shopping Behavior; Two-Way ANOVA; Demographic Predictors; Age-Income Interaction; E-Commerce in NCR.

### 1. INTRODUCTION

India's consumer landscape has undergone a profound digital transformation over the past decade. The rise of mobile internet access, real-time payment systems, and e-commerce platforms has redefined how consumers interact with retail. Among India's metropolitan zones, the National Capital Region (NCR) stands out as a testing ground for new digital consumption behaviors. As Goyal (2024) observes, "quick commerce" platforms promising near-instant delivery have rapidly shifted the benchmark of convenience in urban India.

The acceleration of e-retail adoption in NCR is driven not just by infrastructure, but also by behavioral adaptation across income and education groups. Akther (2023) highlights the role of delivery networks and consumer trust in sustaining e-commerce growth, while Koli et al. (2023) report that app-based transactions and digital payment systems like UPI have made e-shopping more accessible across socio-economic categories. These shifts have blurred traditional distinctions between digital 'early adopters' and the mainstream market.

Despite this mainstreaming of e-commerce, much of the existing academic literature continues to rely on demographic segmentation as its core explanatory framework. Seminal studies like Rambhi, Saerang, and Rumokoy (2014) and Özkan (2015) treat age, gender, income, and education as the primary predictors of online shopping behavior. In similar fashion, Hossain et al. (2022) linked purchase intent to demographic traits in the Bangladeshi market, reflecting a broader reliance on static population variables to model digital consumption patterns.

However, growing empirical evidence calls this demographic determinism into question. Gami et al. (2024) report that variables such as education and age correlate only weakly with behaviors like product comparison, cart abandonment, or loyalty in e-retail environments. In a focused study of NCR-based consumers, Rajvanshi (2021) observed that intent to purchase was shaped more by platform familiarity and past shopping experience than by income or education level.

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Similarly, Abir et al. (2020) found that delivery reliability and user interface ease played a stronger role than demographic factors in shaping online shopping behavior in Dhaka.

This emerging critique highlights a key gap in the literature: most models fail to account for interactional effects—for instance, how age might amplify or reduce the impact of income on digital purchasing. As Shahzad (2015) argues, digital comfort and shopping history often mediate the influence of traditional demographic markers. Sodadasi and Polepeddi (2016) extend this argument by showing that psychographic traits such as lifestyle, tech enthusiasm, and perceived convenience outperform income or education in predicting consumer choices.

To address this gap, recent researchers have proposed more nuanced frameworks that blend structural and behavioral variables. Vijayarathy (2004) advocates segmenting consumers based on digital motivations and risk profiles rather than income brackets. Dahiya (2012) likewise reports that perceived usefulness, platform trust, and transaction transparency explain online behavior better than educational qualifications. These insights point to the importance of analyzing not just individual traits, but also how they interact with behavioral and satisfaction-related factors in shaping e-commerce adoption.

This study adopts that layered approach by evaluating both demographic factors (age, income, education) and interactional influences (e.g., Age  $\times$  Income, Education  $\times$  Advertisement, Social Media  $\times$  Ad Exposure) using One-Way and Two-Way ANOVA. Rather than assuming demographic traits to be universal predictors, the research investigates whether their predictive power holds when tested alongside digital behavior variables such as payment preferences, delivery satisfaction, and media engagement.

## Research Objectives and Hypotheses

**Objective 1:** To identify the influencing factors of consumer satisfaction from retail shopping to e-shopping in NCR.

**Objective 2:** To examine the relationship among influencing factors toward e-shopping.

To operationalize these objectives within a statistically testable framework, the following null hypotheses were formulated:

**Hypothesis 1 (H1):** Education does not influence the online purchasing decisions of NCR consumers.

**Hypothesis 2 (H2):** Income has no substantial impact on the frequency of online purchases in NCR.

These hypotheses are examined using both One-Way and Two-Way ANOVA to assess not only the independent effects of demographic factors but also how they interact with behavioral and contextual variables to shape online shopping preferences.

## 2. Methodology

### 2.1 Research Design

This study employed a quantitative, cross-sectional, and analytical research design to investigate the demographic and interactional predictors of online shopping behavior in the National Capital Region (NCR) of India. The design was selected to capture behavioral patterns at a single point in time, while allowing for the use of inferential statistics to test hypotheses related to both independent effects and interactional dynamics. Given the multidimensional scope of the study-encompassing consumer perception, satisfaction, and behavioral frequency—a combination of descriptive and inferential analytical techniques was adopted.

### 2.2 Population and Sampling

The target population comprised urban and semi-urban consumers residing in the NCR who had engaged in either e-commerce or traditional retail shopping within the preceding three months. Eligible participants were aged between 18 and 65 years and had completed a minimum of 10th standard education to ensure baseline digital comprehension.

A two-stage non-probability sampling strategy was adopted. In the first stage, purposive sampling was used to recruit participants from high-footfall commercial and public locations, including shopping malls, colleges, metro stations, and local markets across Delhi, Noida, Gurugram, and Faridabad. This approach ensured access to active shoppers from diverse economic and educational backgrounds. In the second stage, snowball sampling was utilized to reach populations less likely to participate in face-to-face surveys—particularly older adults or less digitally engaged users—by leveraging

referrals from initial respondents. This hybrid strategy enabled the study to achieve broad demographic representation while capturing nuanced digital behaviors.

A total of 576 valid responses were obtained, exceeding the minimum recommended sample size for robust One-Way and Two-Way ANOVA testing at a 95% confidence level. This ensured statistical power and allowed for reliable subgroup analysis.

### 2.3 Data Collection Tools

Data were gathered using a structured, close-ended questionnaire consisting of 32 items distributed across six thematic sections aligned with the research objectives. Section A captured demographic variables such as age, gender, education, income, and area of residence. Section B assessed shopping habits and frequency of online versus offline retail engagement. Section C focused on satisfaction drivers including delivery experience, return policies, payment flexibility, and trust in product ratings. Section D examined behavioral influence variables, such as exposure to digital advertisements and social media engagement. Section E explored consumer perceptions and attitudes toward online shopping, while Section F recorded behavioral frequency indicators including repeat purchases and platform preference.

All attitudinal items were measured using a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree), while demographic items were coded using categorical and ordinal scales. The instrument was pre-tested to ensure clarity, content validity, and internal consistency.

The questionnaire was administered via two complementary modes. Face-to-face surveys were conducted using printed forms or digital tablets at selected public locations. In addition, self-administered questionnaires were disseminated digitally using QR codes posted at retail centers, allowing tech-savvy consumers to participate anonymously via mobile devices.

### 2.4 Variables and Measurement

The study's independent variables included demographic factors—namely age, education, and income—as well as behavioral predictors such as delivery time reliability, review and rating influence, return policy experience, and payment convenience. These were operationalized as either categorical or ordinal variables based on the nature of the response format.

The primary dependent variable was the self-reported frequency of online shopping, measured on a 5-point ordinal scale ranging from “Never” to “Frequently.” Additional outcome variables included satisfaction levels, perceived influence of media exposure, and repeat purchase intention. For example, the item “Timely delivery influences my decision to shop online” was used to assess delivery reliability on a 5-point Likert scale, while frequency was captured through the question “How often do you shop online in a month?” measured using ordinal ranges.

#### Example of Variable Mapping

Variable	Sample Item	Scale
Age	"Select your age group"	Categorical
Delivery Time	"Timely delivery influences my decision to shop online"	Likert (1–5)
Shopping Frequency	"How often do you shop online in a month?"	Ordinal
Ad Influence	"Instagram/Facebook ads affect my shopping choices"	Likert (1–5)

### 2.5 Statistical Analysis

Descriptive statistics, including frequency distributions, means, and standard deviations, were used to summarize demographic attributes and overall consumer behavior trends. For inferential analysis, three techniques were employed using SPSS (version 26).

Pearson's correlation coefficient was applied to examine linear relationships between satisfaction-related variables-such as delivery time, reviews, payment methods-and online shopping frequency. One-Way ANOVA was used to identify statistically significant differences in shopping behavior across individual demographic groups (education, income, age). Two-Way ANOVA was conducted to test interaction effects between key variables, including Age  $\times$  Income, Education  $\times$  Advertisement Exposure, and Social Media  $\times$  Advertisement. Both main and interaction effects were interpreted at a significance level of  $p < 0.05$ . Assumptions of normality, independence, and homogeneity of variances were verified, and large sample robustness further supported the validity of the tests.

## 2.6 Ethical Considerations

All participants provided informed consent prior to participation. Respondents were assured that their data would remain anonymous and confidential, and that they could withdraw at any stage without penalty. The study adhered to standard ethical protocols for academic social science research and did not involve any sensitive personal data or invasive procedures.

## 3. RESULTS

### 3.1 Descriptive Profile and Preference Trends

The consumer landscape in the National Capital Region (NCR) reflects a strong inclination toward digital commerce, with the majority of respondents indicating a preference for online over offline retail formats. This trend establishes the contextual baseline for further analysis of the demographic and behavioral predictors influencing e-shopping frequency.

As shown in **Table 1**, out of 542 valid responses, 423 participants (78%) reported that they primarily preferred online shopping platforms, while only 119 respondents (22%) favored traditional offline retail. This skew toward digital platforms suggests that e-commerce has moved beyond early adopter segments and now serves as the dominant shopping channel for a broad cross-section of NCR consumers. The continued presence of an offline-preferring segment, however, highlights the persistent relevance of physical stores-potentially due to personal service preferences, product tangibility, or limited digital literacy among certain consumer groups.

This foundational pattern of consumer preference sets the stage for examining more nuanced influences-such as satisfaction drivers, demographic segmentation, and interactional effects-on shopping frequency and behavior, which are explored in the subsequent sections.

**Table 1. Preferred shopping channel among respondents in the NCR (n = 542)**

Preferred Channel	Frequency	Percentage (%)
Online Shoppers	423	78%
Offline Shoppers	119	22%
<b>Total</b>	<b>542</b>	<b>100%</b>

### 3.2 Satisfaction Predictors of Online Shopping

Consumer satisfaction plays a central role in determining the frequency and consistency of online shopping behavior. In this study, two key satisfaction-related variables-**delivery time** and **payment terms**-were analyzed for their statistical relationship with shopping frequency using Pearson's correlation analysis.

#### Delivery Time

Timely delivery is frequently cited as a critical determinant of consumer satisfaction in e-commerce. The correlation between perceived delivery speed and frequency of online purchases is presented in **Table 2**. The Pearson correlation coefficient is **-0.099**, with a **p-value of 0.043**, indicating a statistically significant but weak negative relationship.

This result suggests that faster delivery is modestly associated with increased shopping frequency; however, the influence is limited in magnitude. The weak negative coefficient may reflect that delivery expectations are already normalized

across platforms in urban NCR, thereby reducing its differential impact on behavior. Nonetheless, even small gains in delivery speed may reinforce trust and encourage repeat engagement in a competitive digital retail environment.

**Table 2. Pearson correlation between delivery time and frequency of online purchases (n = 423)**

Variable Factor	Frequency of Online Purchase	Delivery Time
Pearson Correlation	1	-0.099
Sig. (2-tailed)	–	0.043
N	423	423

### Payment Terms

Flexible and trusted payment mechanisms are often considered enablers of digital commerce. To test their behavioral relevance, the relationship between payment terms and online shopping frequency was analyzed (see **Table 3**). The correlation coefficient is **0.091** with a **p-value of 0.077**, suggesting a positive but statistically non-significant association.

This implies that while convenient payment options such as UPI, digital wallets, and cash on delivery may contribute to initial adoption or user confidence, they do not appear to substantially affect how frequently consumers engage in online shopping once familiar with the platform. The result reinforces the idea that in digitally mature markets like NCR, payment flexibility functions more as a transactional facilitator than as a behavioral driver.

**Table 3. Pearson correlation between payment terms and online shopping behavior (n = 377)**

Variable Factor	Shopping Behavior	Payment Terms
Pearson Correlation	1	0.091
Sig. (2-tailed)	–	0.077
N	377	377

### 3.3 Structural Demographic Predictors of Online Shopping Behavior

Demographic characteristics-particularly **education** and **income**-have traditionally been regarded as key predictors of digital shopping behavior. This section evaluates their isolated influence on shopping frequency using One-Way ANOVA, thereby directly addressing **Objective 1** and testing **Hypotheses 1 and 2**.

#### 3.3.1 Influence of Educational Attainment

To assess whether educational background affects the frequency of online shopping, a One-Way ANOVA was conducted using four education categories: Matriculation, 12th Standard, Graduation, and Post-Graduation. The descriptive statistics (see **Table 4**) reveal that the standard deviation of online shopping frequency across education levels ranged narrowly from 0.905 to 1.115, indicating uniform variability within groups and suitability for ANOVA analysis.

As shown in **Table 5**, the ANOVA results yielded an **F-value of 0.672** with a **p-value of 0.570**, which is well above the 0.05 significance threshold. These findings support **Hypothesis 1 (H1): Education does not influence the online purchasing decisions of NCR consumers**. The non-significant result implies that online shopping frequency is largely unaffected by educational qualifications in the studied population.

This outcome is notable in the context of increasing digital accessibility in India, where app-based shopping interfaces, vernacular options, and mobile-first platforms have reduced the education-based digital divide. These results suggest that behavioral or psychographic segmentation may offer more actionable insights than education-based targeting.

**Table 4. Standard deviation of online shopping frequency across education levels (n = 423)**

Highest Level of Education	N	Standard Deviation
Matriculation	27	1.115
12th Standard	131	0.968
Graduation	193	0.905
Post-Graduation	72	0.954
<b>Total</b>	<b>423</b>	<b>0.946</b>

**Table 5. One-way ANOVA for education levels and frequency of online purchases**

Source	df	Mean Square	F	Sig. (p-value)
Between Groups	3	0.603	0.672	0.570
Within Groups	419	0.897		
<b>Total</b>	<b>422</b>			

### 3.3.2 Influence of Income Level

The relationship between household income and shopping frequency was also evaluated using One-Way ANOVA. Respondents were grouped into five income brackets: Less than ₹20,000; ₹20,000–50,000; ₹50,000–1,00,000; ₹1,00,000–1,50,000; and More than ₹1,50,000. As shown in **Table 6**, standard deviations across groups were narrowly clustered between 0.902 and 0.975, satisfying ANOVA assumptions.

The results in **Table 7** reveal an **F-value of 1.267** with a **p-value of 0.282**, indicating no statistically significant difference in online shopping frequency across income levels. This supports **Hypothesis 2 (H2): Income has no substantial impact on the frequency of online purchases in NCR.**

This finding underscores a broader trend in e-commerce diffusion: income is becoming less predictive of online shopping frequency in regions with high digital penetration. The wide availability of budget-friendly platforms, EMI options, and discount-heavy campaigns may explain why online shopping is no longer the domain of higher-income segments alone.

**Table 6. Standard deviation of online shopping frequency across income groups (n = 423)**

Monthly Household Income (INR)	N	Standard Deviation
Less than ₹20,000	54	0.964
₹20,000–50,000	111	0.926
₹50,000–1,00,000	108	0.975
₹1,00,000–1,50,000	66	0.965
More than ₹1,50,000	84	0.902
<b>Total</b>	<b>423</b>	<b>0.946</b>

**Table 7. One-way ANOVA for income level and frequency of online purchases**

Source	df	Mean Square	F	Sig. (p-value)
Between Groups	4	1.267	1.267	0.282

Within Groups	418	0.891		
<b>Total</b>	<b>422</b>			

### 3.4 Interactional Predictors of Online Shopping Behavior

While individual demographic variables such as income or education showed limited predictive power in isolation, online shopping behavior may be shaped more meaningfully by interactional effects-combinations of demographic and behavioral traits. This section explores how variables such as age, income, education, advertisement exposure, and social media activity interact to influence digital purchase behavior, in alignment with Objective 2 of the study.

#### 3.4.1 Education × Income Interaction

The interaction between education level and income was assessed to examine whether their combined influence significantly affects shopping behavior. As shown in **Table 8**, neither education ( $p = 0.213$ ), income ( $p = 0.136$ ), nor their interaction ( $p = 0.892$ ) yielded statistically significant results.

These findings reinforce earlier observations from One-Way ANOVA: both education and income-individually or in combination-do not meaningfully impact shopping frequency. This underscores the shifting paradigm in e-commerce, where digital behaviors increasingly transcend traditional socio-economic boundaries.

**Table 8. Two-Way ANOVA between education, income, and online shopping preferences**

Source	df	Mean Square	F	Sig.
Education	3	0.157	1.505	0.213
Income	4	0.184	1.759	0.136
Education × Income	11	0.054	0.516	0.892

#### 3.4.2 Education × Age Interaction

To explore generational effects on the influence of education, a Two-Way ANOVA was conducted using age and education as factors. As presented in **Table 9**, **education** had a statistically significant effect ( $p = 0.039$ ), while **age** and the **interaction term** were not significant ( $p = 0.275$  and  $p = 0.106$ , respectively).

This suggests that although education may independently affect shopping preferences to some extent, its impact is not moderated by age. In other words, generational variation does not amplify or reduce the effect of education on shopping behavior.

**Table 9. Two-Way ANOVA between education, age, and online shopping preferences**

Source	df	Mean Square	F	Sig.
Education	3	0.291	2.815	0.039
Age	3	0.134	1.296	0.275
Education × Age	7	0.177	1.705	0.106

#### 3.4.3 Age × Income Interaction

The strongest interactional effect in the study emerged from the relationship between income and age, as shown in **Table 10**. While income had a statistically significant effect ( $p = 0.0055$ ), the **interaction between age and income** was even more robust ( $p = 0.0002$ ).

These findings suggest that income’s impact on shopping behavior is not uniform across all age groups. For example, younger consumers with lower incomes may be more engaged in online shopping than older, high-income groups. This reinforces the need for **age-income segmentation** in marketing strategies and highlights the limits of treating income as a standalone predictor.

**Table 10. Two-Way ANOVA between income, age, and online purchase behavior**

Source	df	Mean Square	F	Sig.
Age	3	0.065	0.6436	0.5874
Income	4	0.376	3.7258	0.0055
Age × Income	11	0.334	3.3086	0.0002

### 3.4.4 Age × Advertisement Exposure

Digital advertising is often tailored by platform algorithms based on user age and browsing behavior. In this study, **age** was found to significantly influence receptiveness to online advertisements ( $p = 0.021$ ), while **education** and the **interaction term** were not significant (see **Table 11**).

This implies that online advertisement strategies should be age-responsive rather than education-based. Younger users may respond differently to visual or influencer-driven ads compared to older users who may prefer informational formats.

**Table 11. Two-Way ANOVA between age, education, and advertisement influence**

Source	df	Mean Square	F	Sig.
Age	3	0.668	3.2760	0.0210
Education	3	0.403	1.9760	0.1170
Age × Education	6	0.289	1.4180	0.2070

### 3.4.5 Social Media × Advertisement Influence

Finally, the interaction between **social media activity** and **advertisement influence** was tested to evaluate their combined effect on shopping frequency. As reported in **Table 12**, none of the individual or joint effects were statistically significant ( $p > 0.1$  for all).

This finding indicates that, in the NCR context, being active on social media or encountering ads on these platforms does not independently or jointly predict how frequently consumers shop online. This may reflect consumer desensitization to routine ad exposure or selective engagement with sponsored content.

**Table 12. Two-Way ANOVA between social media activity, advertisement influence, and shopping frequency**

Source	df	Mean Square	F	Sig.
Active Social Media	2	1.817	2.0020	0.1360
Advertisement Influence	1	0.160	0.1760	0.6750
Active Social Media × Advertisement Influence	2	0.823	0.9070	0.4050

#### 4. DISCUSSION

This study investigated the demographic and interactional predictors that influence the frequency of online shopping among consumers in the National Capital Region (NCR) using a layered statistical approach. The findings challenge longstanding assumptions in consumer research, particularly regarding the predictive power of education and income on e-shopping behavior. The results from One-Way ANOVA indicate that neither educational attainment ( $F = 0.672$ ,  $p = 0.570$ ; **Table 5**) nor income level ( $F = 1.267$ ,  $p = 0.282$ ; **Table 7**) exerts a statistically significant influence on the frequency of online purchases. These outcomes support the null hypotheses H1 and H2, which state that education and income do not meaningfully affect digital purchase behavior in the NCR context.

These results are supported by a narrow variance in consumer behavior across demographic segments, as seen in the standard deviations reported in **Table 4** (education) and **Table 6** (income). Such convergence suggests that factors like increasing smartphone penetration, simplified interfaces, mobile payments, and vernacular accessibility have effectively flattened digital divides once shaped by socioeconomic status. Studies by Odike et al. (2019) and Arisah et al. (2016) similarly found that education had no significant bearing on online shopping habits in digitally expanding economies. Mishra (2016) reached parallel conclusions regarding income, emphasizing how digital ecosystems are now inclusive of low- and mid-income users, especially in urban Indian contexts.

In line with this, the findings suggest a shift from traditional demographic targeting to psychographic and behavioral segmentation. As Basalma (2024) and Punj (2012) point out, attributes such as device familiarity, convenience orientation, and responsiveness to platform incentives are now more reliable indicators of consumer behavior than education or income alone. The implication is that marketers and platform designers may benefit more from micro-level behavioral data than from broad demographic profiling.

However, the interaction between income and age emerged as a statistically significant predictor of online shopping frequency. According to the Two-Way ANOVA results (**Table 10**), both income alone ( $p = 0.0055$ ) and the interaction term Age  $\times$  Income ( $p = 0.0002$ ) were found to significantly influence digital shopping behavior. This suggests that income does not exert a uniform effect across all age groups, and its impact is significantly moderated by generational factors. For example, younger consumers with lower income may exhibit greater online shopping frequency than older, high-income individuals, possibly due to differences in digital literacy, risk aversion, or interface adaptability.

This finding aligns with prior literature, including Rummo et al. (2022) and Rajvanshi (2021), both of whom noted that age amplifies or suppresses the behavioral outcomes typically associated with income in online shopping contexts. Sorce et al. (2005) similarly found that younger individuals, regardless of income, were more responsive to digital purchasing platforms than older users. These studies corroborate the need for cross-cutting segmentation based on age-income combinations rather than treating these variables in isolation.

Other interactional predictors such as Education  $\times$  Income (**Table 8**), Education  $\times$  Age (**Table 9**), and Social Media  $\times$  Advertisement (**Table 12**) did not yield statistically significant effects. This strengthens the argument that Age  $\times$  Income is a uniquely powerful intersectional driver of behavior. As Ortega et al. (2011) warned, high-income consumers are not a monolithic group-failing to disaggregate by age can lead to poor predictive accuracy. This insight was further reinforced by Rahman and Yu (2019), who emphasized that motivations differ greatly even within similar income brackets when age is factored in.

The study also tested the influence of digital marketing exposure on consumer behavior. Despite widespread assumptions in e-commerce literature, neither social media activity nor perceived advertisement influence significantly impacted shopping frequency, as shown by the nonsignificant outcomes in **Table 12**. These findings suggest that visibility and platform engagement alone are insufficient to trigger behavioral outcomes. Rather, they support the growing body of work suggesting that personalization and contextual targeting are more critical than raw ad exposure. Studies by Nasidi et al. (2021), Janitrafia and Ruswanti (2024), and Wang (2023) affirm that consumer attention does not reliably convert to purchasing behavior unless ads are delivered in highly personalized and context-sensitive formats.

The weak results from **Table 12** are consistent with recent observations of digital fatigue, especially among younger, ad-saturated users. Geofani et al. (2024) reported that increased ad exposure on platforms like Instagram and Facebook leads to declining responsiveness due to repetition and perceived irrelevance. This reflects a decoupling between social media

engagement and actual consumption behavior, an idea echoed by V.J. and Thanushree (2020), who note that ad views and likes rarely translate into actual buying decisions unless aligned with consumer intent and timing.

In contrast, the satisfaction predictors-delivery time and payment terms-revealed more practical insights, albeit with modest influence. As shown in **Table 2**, delivery time had a weak negative but statistically significant correlation with shopping frequency ( $r = -0.099$ ,  $p = 0.043$ ). Faster deliveries appear to be associated with slightly higher purchasing frequency, supporting the view that convenience factors continue to reinforce consumer trust and retention in mature e-commerce markets. On the other hand, **Table 3** indicates that payment terms showed a weak and statistically non-significant correlation ( $r = 0.091$ ,  $p = 0.077$ ) with shopping frequency, suggesting that while flexibility in payment methods is important for adoption, it is not a decisive factor in ongoing behavior.

## 5. CONCLUSION

Together, these satisfaction metrics indicate that the NCR's online shoppers are now accustomed to high service standards, and only incremental improvements-such as reduced delivery times or seamless checkout experiences-have measurable behavioral consequences. While initial adoption may have depended on payment convenience and trust, long-term frequency appears to be governed more by platform experience and behavioral alignment.

Collectively, the findings from this study demonstrate that the future of digital consumer engagement lies in intersectional and behavioral modeling, rather than in conventional demographic profiling. The integration of nuanced age-income interactions, weak influence of marketing exposure, and moderate satisfaction predictors underscores a maturing e-commerce environment in NCR that demands both strategic segmentation and experience-based differentiation.

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### Conflict of Interest

The authors declare that there is no conflict of interest.

### Author Contributions

*Renuka Yadav* (First Author, PhD Scholar): Designed the study, developed the questionnaire, collected the data, performed statistical analysis, interpreted results, and wrote the manuscript.

*Dr. Deepak Dixit* (Supervisor): Provided academic supervision, guided research methodology, reviewed analytical findings, and critically revised the manuscript.

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