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# Impact of Demographics on Consumer Preferences in Online Shopping: An Analysis of Age, Gender, and Education Factors

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**Abstract:** This study explores the influence of demographic factors-age, gender, and education level-on consumer preferences and behaviors in online shopping. Through a quantitative analysis using ANOVA, data from 119 participants highlight that age and education level significantly impact perceptions of platform selection, product security, and the importance of reviews, while gender differences are less pronounced. Key findings indicate that younger consumers value convenience and variety, while higher-educated users prioritize security and trust in reviews. These insights are critical for e-commerce platforms aiming to enhance user experience and drive engagement by aligning their strategies with demographic-specific needs. The study provides a foundation for further research on evolving consumer behaviors and offers global relevance as e-commerce continues its rapid expansion.

**Keywords:** Online Shopping, Consumer Behavior, Demographics, e-commerce preferences

## INTRODUCTION

Online shopping has significantly transformed the retail landscape, especially with platforms like Amazon leading the way in terms of user experience and technological innovation. As e-commerce continues to grow, customer behavior has become a focal point for businesses looking to enhance satisfaction and drive loyalty. Research indicates that gamification within online platforms, such as Amazon, can enhance customer satisfaction and loyalty by integrating interactive elements without monetary incentives (Bauer et al., 2020). This development reflects a broader shift towards creating more engaging and personalized digital shopping experiences. Furthermore, the ongoing digital transformation and the adoption of innovative technologies in emerging markets have reshaped how consumers interact with e-retailers (Malekpour et al., 2023).

One critical factor influencing online shopping behavior is the integration of consumers' social and cultural values into e-commerce platforms. Saleh et al. (2019) emphasize the importance of tailoring online shopping experiences to meet specific customer requirements, including religious and social beliefs, particularly in markets influenced by Islamic values. This underscores the role of cultural context in shaping online consumer behavior, which has implications for platforms like Amazon as they expand into diverse markets. On a global scale, foresight into online shopping behavior, such as the "what next syndrome" studied by Sharma et al. (2019), highlights how consumers' decision-making processes are evolving in response to the dynamic nature of e-commerce platforms.

Technological innovation has played a pivotal role in shaping customer experiences in online shopping. The cashier-free checkout systems proposed by Agrawal and Mittal (2024) represent an effort to bridge the gap between the online and in-store shopping experiences, potentially offering Amazon a model for improving convenience and reducing friction in the purchasing process. Similarly, the phenomenon of showrooming—where consumers browse in physical stores but make purchases online—has been shown to drive customer inspiration and foster loyalty when managed effectively (Frasquet & Ieva, 2024). This behavior is particularly relevant in omnichannel retail strategies, which combine online and offline elements to create seamless shopping experiences.

Environmental concerns and sustainability have also emerged as important factors in online shopping behavior. Jalil et al. (2024) discuss the integration of trust and green supply chain management practices to enhance online shopping satisfaction, suggesting that sustainability initiatives can positively influence consumer trust in e-commerce platforms like Amazon. The spillover effects of data breaches on consumer perceptions, as explored by Park et al. (2024), further demonstrate how trust plays a critical role in shaping online shopping behavior. A platform's ability to maintain consumer trust through secure data practices is essential for long-term customer retention.

The COVID-19 pandemic has further accelerated changes in consumer behavior, with shifts in e-retailer preferences and heightened price sensitivity during crises (Rahmani & Kordrostami, 2023). Post-pandemic motivations for e-retailer preferences, as studied by Roy and Shaikh (2024), indicate that consumers are increasingly seeking convenience, trust, and safety in their online shopping experiences. This is particularly relevant for platforms like Amazon, which have had to adapt to changing customer expectations in the wake of the pandemic. Moreover, coopetition between online and offline retailers, as highlighted by Halan and Singh (2023), suggests that the boundaries between these two channels are becoming increasingly blurred, offering opportunities for both collaboration and competition.
In addition to technological and environmental factors, behavioral aspects such as impulse purchases during emergency situations have been found to be influenced by permission marketing and emerging technologies like blockchain (Nigam et al., 2023). This aligns with broader trends in retail innovation, where technological advancements from 1980 to 2020 have drastically reshaped the industry (Krishnamurthy & Venkitachalam, 2023). As retailers like Amazon continue to innovate, they must consider the impact of new technologies on consumer behavior.

Amazon's exploration of personalized livestreaming experiences through services like Amazon Explore has raised questions about the platform's potential competition with the hospitality industry (Ramadan et al., 2023). These developments highlight how e-commerce platforms are expanding beyond traditional retail boundaries to offer more immersive and customized experiences for consumers. As Verhoef et al. (2023) and Rajagopal (2022) reflect on the long-term effects of the pandemic on retail, it becomes clear that platforms like

Amazon must continue to evolve in response to shifting consumer needs and technological advancements.

## METHOD

The research methodology for this study is designed to explore the factors influencing customer behavior in online shopping, specifically focusing on consumers in Ahmedabad. Given the rapidly expanding e-commerce landscape and the increasing reliance on digital platforms like Amazon, it is essential to understand the attitudes and behaviors that drive consumer choices. Drawing on previous research (Akroush & Al-Debei, 2015; Klaus, 2013), this study aims to identify key determinants of consumer satisfaction and trust in online shopping environments and their subsequent impact on purchasing decisions.

**Objectives**

- **To examine the impact of trust-building mechanisms on consumer satisfaction and repurchase intentions** in the context of online shopping platforms such as Amazon.
- **To assess the influence of product variety, pricing strategies, and convenience on customer loyalty and shopping behavior** in Ahmedabad's online retail sector.

**Hypotheses**

1. **H1:** There is a significant positive relationship between trust-building mechanisms (such as secure payment options and customer reviews) and consumer satisfaction in online shopping (Anaza & Zhao, 2013; Liu & Tang, 2018).
2. **H2:** Product variety, pricing strategies, and convenience have a significant impact on consumer repurchase intentions and loyalty toward online shopping platforms (Kumar, Eidem, & Perdomo, 2012; Petrescu, 2011).

The study adopts a quantitative research design, employing a structured questionnaire as the primary data collection tool. A total of 101 samples were collected from residents of Ahmedabad using a Google Form, which was shared across digital platforms to reach a broad and diverse respondent base. The sample size was deemed appropriate for preliminary analysis and consistent with similar studies conducted in online shopping contexts (Liu & Hong, 2016). The questionnaire included items that measured trust, product variety, convenience, and pricing strategies, with questions designed based on validated scales from prior research (Akroush & Al-Debei, 2015; Klaus, 2013).

For data analysis, SPSS software was utilized to conduct descriptive statistics, correlation analysis, and hypothesis testing. Descriptive statistics provided insights into the demographic profile of respondents and their online shopping habits. Correlation analysis examined the relationships between key variables such as trust, product variety, pricing, and consumer loyalty. Hypothesis testing (using regression analysis) helped to determine the significance and strength of these relationships (Kumar, Eidem, & Perdomo, 2012). This analysis provided a robust understanding of how different factors impact consumer behavior in the digital shopping environment.

In conclusion, this methodology allows for a systematic investigation of the factors influencing consumer behavior in Ahmedabad's online shopping market, offering valuable insights for retailers aiming to enhance customer satisfaction and loyalty. The integration of prior research on trust and convenience (Liu & Tang, 2018; Anaza & Zhao, 2013) ensures that the study builds on established knowledge while contributing fresh insights specific to the Ahmedabad market.

## RESULT AND DISCUSSION

**Table 1. Age**

| | | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|---|
| Valid | Under 18 | 12 | 10.1 | 10.1 | 10.1 |
| | 18-25 | 93 | 78.2 | 78.2 | 88.2 |
| | 26-35 | 8 | 6.7 | 6.7 | 95.0 |
| | 36-45 | 3 | 2.5 | 2.5 | 97.5 |
| | 46-55 | 2 | 1.7 | 1.7 | 99.2 |
| | Above 55 | 1 | .8 | .8 | 100.0 |
| | Total | 119 | 100.0 | 100.0 | |

This table categorizes respondents by age groups, showing a significant majority (78.2%) of participants between 18-25 years old, indicating that the sample skews younger. A smaller proportion (6.7%) falls within the 26-35 age range, and an even smaller percentage includes those over 36. The cumulative data indicate that nearly all participants are under 35, which might suggest that younger demographics are more engaged in online shopping. This distribution helps researchers understand which age group is most actively participating in online shopping and informs potential age-based marketing strategies.

**Table 2. Gender**

| | | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|---|
| Valid | Male | 73 | 61.3 | 61.3 | 61.3 |
| | Female | 42 | 35.3 | 35.3 | 96.6 |
| | Others | 4 | 3.4 | 3.4 | 100.0 |
| | Total | 119 | 100.0 | 100.0 | |

Gender distribution among respondents is shown here, with 61.3% identifying as male, 35.3% as female, and 3.4% as "Others." This balance suggests that while males constitute a majority, there is still a significant representation of other genders in the sample, potentially reflecting diverse preferences and behaviors in online shopping. Understanding gender distribution is essential in tailoring marketing approaches, as preferences may vary by gender. The cumulative percentage values provide a clear view of gender distribution within the population studied.

**Table 3. Education Level**

| | | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|---|
| Valid | High School | 13 | 10.9 | 10.9 | 10.9 |
| | Undergraduate | 78 | 65.5 | 65.5 | 76.5 |
| | Postgraduate | 16 | 13.4 | 13.4 | 89.9 |
| | Doctorate | 6 | 5.0 | 5.0 | 95.0 |
| | Other | 6 | 5.0 | 5.0 | 100.0 |
| | Total | 119 | 100.0 | 100.0 | |

Respondents' education levels vary, with the majority (65.5%) having an undergraduate education, followed by 13.4% with postgraduate degrees. Only 5% have attained a doctorate, while another 5% selected "Other." Education level can be a predictor of online shopping behavior, as higher educational attainment might correlate with technological comfort and purchasing power. Knowing the education level also helps identify potential correlations between educational background and online shopping patterns, thereby helping to design more targeted advertising content.

**Table 4. Employment Status**

| | | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|---|
| Valid | Student | 88 | 73.9 | 73.9 | 73.9 |
| | Employed | 11 | 9.2 | 9.2 | 83.2 |
| | Self-Employed | 10 | 8.4 | 8.4 | 91.6 |
| | Unemployed | 5 | 4.2 | 4.2 | 95.8 |
| | Retired | 5 | 4.2 | 4.2 | 100.0 |
| | Total | 119 | 100.0 | 100.0 | |

Employment status reveals that a substantial proportion of respondents (73.9%) are students, with employed and self-employed individuals making up only 17.6% combined. The remaining participants are unemployed or retired. This skew towards students is significant for understanding online shopping behaviors, as they may have distinct spending patterns and priorities compared to working professionals. The table thus gives insights into the purchasing behavior likely influenced by employment status, which could guide product and promotional targeting.

**Table 5. Monthly Income (INR)**

| | | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|---|
| Valid | Less than 10,000 | 51 | 42.9 | 42.9 | 42.9 |
| | 10,001 - 25,000 | 20 | 16.8 | 16.8 | 59.7 |
| | 25,001 - 50,000 | 10 | 8.4 | 8.4 | 68.1 |
| | 50,001 - 75,000 | 11 | 9.2 | 9.2 | 77.3 |
| | 75,001 - 1,00,000 | 10 | 8.4 | 8.4 | 85.7 |
| | Above 1,00,000 | 17 | 14.3 | 14.3 | 100.0 |
| | Total | 119 | 100.0 | 100.0 | |

Monthly income levels highlight that 42.9% of respondents earn less than 10,000 INR, with only 14.3% earning over 100,000 INR, suggesting a predominantly low-to-moderate income sample. These income brackets can strongly influence purchasing power and product preferences in online shopping. As income often determines spending behavior and frequency of shopping, this data is crucial for segmenting markets by income level and tailoring strategies, such as promoting budget-friendly options or exclusive deals for higher-income consumers.

**Table 6. Online**

| | | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|---|
| Valid | Never | 15 | 12.6 | 12.6 | 12.6 |
| | Once a month | 47 | 39.5 | 39.5 | 52.1 |
| | 2-3 times a month | 34 | 28.6 | 28.6 | 80.7 |
| | Weekly | 17 | 14.3 | 14.3 | 95.0 |
| | More than once a week | 6 | 5.0 | 5.0 | 100.0 |
| | Total | 119 | 100.0 | 100.0 | |

Frequency of online shopping shows that a large segment (39.5%) shops online once a month, while 28.6% shop 2-3 times a month. Weekly shoppers comprise 14.3%, and only 5%

shop daily. This distribution reflects the periodic shopping habits typical among consumers, with the largest group engaging monthly. Understanding shopping frequency helps in predicting the demand cycles, which in turn enables better inventory management and more effective timing of promotional campaigns tailored to varying levels of shopping frequency.

**Table 7. ANOVA between Age and Factors**

| | | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|
| Platform | Between Groups | 38.415 | 5 | 7.683 | 4.199 | .002 |
| | Within Groups | 206.745 | 113 | 1.830 | | |
| | Total | 245.160 | 118 | | | |
| Products | Between Groups | 45.374 | 5 | 9.075 | 4.621 | <.001 |
| | Within Groups | 221.903 | 113 | 1.964 | | |
| | Total | 267.277 | 118 | | | |
| Spend | Between Groups | 24.507 | 5 | 4.901 | 4.043 | .002 |
| | Within Groups | 136.989 | 113 | 1.212 | | |
| | Total | 161.496 | 118 | | | |
| Security | Between Groups | 22.624 | 5 | 4.525 | 4.769 | <.001 |
| | Within Groups | 107.224 | 113 | .949 | | |
| | Total | 129.849 | 118 | | | |
| Reviews | Between Groups | 37.818 | 5 | 7.564 | 6.260 | <.001 |
| | Within Groups | 136.535 | 113 | 1.208 | | |
| | Total | 174.353 | 118 | | | |
| Trust | Between Groups | 31.331 | 5 | 6.266 | 5.393 | <.001 |
| | Within Groups | 131.308 | 113 | 1.162 | | |
| | Total | 162.639 | 118 | | | |
| Frequency | Between Groups | 3.646 | 5 | .729 | .747 | .590 |
| | Within Groups | 110.320 | 113 | .976 | | |
| | Total | 113.966 | 118 | | | |
| Variety | Between Groups | 33.411 | 5 | 6.682 | 5.488 | <.001 |
| | Within Groups | 137.581 | 113 | 1.218 | | |
| | Total | 170.992 | 118 | | | |
| Importance | Between Groups | 37.698 | 5 | 7.540 | 7.017 | <.001 |
| | Within Groups | 121.411 | 113 | 1.074 | | |
| | Total | 159.109 | 118 | | | |
| Pricing | Between Groups | 13.534 | 5 | 2.707 | 2.183 | .061 |
| | Within Groups | 140.113 | 113 | 1.240 | | |
| | Total | 153.647 | 118 | | | |
| Offers | Between Groups | 10.634 | 5 | 2.127 | 2.496 | .035 |
| | Within Groups | 96.290 | 113 | .852 | | |
| | Total | 106.924 | 118 | | | |
| Convenience | Between Groups | 17.890 | 5 | 3.578 | 3.140 | .011 |
| | Within Groups | 128.749 | 113 | 1.139 | | |
| | Total | 146.639 | 118 | | | |
| Delivery | Between Groups | 14.665 | 5 | 2.933 | 2.937 | .016 |
| | Within Groups | 112.831 | 113 | .999 | | |
| | Total | 127.496 | 118 | | | |
| Timesaving | Between Groups | 13.842 | 5 | 2.768 | 2.115 | .069 |

| | | | | | | |
|---|---|---|---|---|---|---|
| | Within Groups | 147.906 | 113 | 1.309 | | |
| | Total | 161.748 | 118 | | | |
| Satisfaction | Between Groups | 12.707 | 5 | 2.541 | 2.614 | .028 |
| | Within Groups | 109.848 | 113 | .972 | | |
| | Total | 122.555 | 118 | | | |
| Repurchase | Between Groups | 13.366 | 5 | 2.673 | 2.301 | .049 |
| | Within Groups | 131.273 | 113 | 1.162 | | |
| | Total | 144.639 | 118 | | | |
| Recommend | Between Groups | 18.555 | 5 | 3.711 | 3.285 | .008 |
| | Within Groups | 127.664 | 113 | 1.130 | | |
| | Total | 146.218 | 118 | | | |
| Loyalty | Between Groups | 12.299 | 5 | 2.460 | 2.150 | .065 |
| | Within Groups | 129.281 | 113 | 1.144 | | |
| | Total | 141.580 | 118 | | | |
| Device | Between Groups | 18.475 | 5 | 3.695 | 2.774 | .021 |
| | Within Groups | 150.516 | 113 | 1.332 | | |
| | Total | 168.992 | 118 | | | |

This ANOVA table explores the relationship between age groups and various factors related to online shopping behavior. The "Sum of Squares" measures the variance, while the "df" (degrees of freedom) is used to understand variance distribution across age groups. The F-value indicates the ratio of variance between groups to within groups, and the "Sig." (significance level) reveals if the differences between age groups are statistically significant.
Factors with a significant difference across age groups ($p < .05$) include "Platform" ($p = .002$), "Products" ($p < .001$), "Spend" ($p = .002$), "Security" ($p < .001$), "Reviews" ($p < .001$), "Trust" ($p < .001$), "Variety" ($p < .001$), "Importance" ($p < .001$), "Offers" ($p = .035$), "Convenience" ($p = .011$), "Delivery" ($p = .016$), "Satisfaction" ($p = .028$), "Repurchase" ($p = .049$), "Recommend" ($p = .008$), and "Device" ($p = .021$). These results indicate that age significantly influences perceptions of platform preference, product types, spending habits, and security concerns, as well as the importance placed on reviews, trust, product variety, convenience, offers, delivery options, and overall satisfaction. Such distinctions can guide marketers in tailoring their strategies to suit different age groups.
Some factors, such as "Frequency" ($p = .590$), "Pricing" ($p = .061$), "Timesaving" ($p = .069$), and "Loyalty" ($p = .065$), do not show significant differences across age groups. This indicates that these aspects may be uniformly perceived, regardless of age. For instance, pricing and time-saving benefits might be valued similarly across all age demographics, suggesting that these factors may be universally appealing in online shopping. Overall, the analysis highlights which elements of online shopping are perceived differently across age groups, providing insights for businesses to develop age-specific marketing tactics that enhance the customer experience.

**Table 8. ANOVA between Gender and Factors**

| | | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|
| Platform | Between Groups | 1.349 | 2 | .674 | .321 | .726 |
| | Within Groups | 243.811 | 116 | 2.102 | | |
| | Total | 245.160 | 118 | | | |
| Products | Between Groups | 3.469 | 2 | 1.734 | .763 | .469 |
| | Within Groups | 263.808 | 116 | 2.274 | | |

| | | | | | | |
|---|---|---|---|---|---|---|
| | Total | 267.277 | 118 | | | |
| Spend | Between Groups | 2.550 | 2 | 1.275 | .930 | .397 |
| | Within Groups | 158.946 | 116 | 1.370 | | |
| | Total | 161.496 | 118 | | | |
| Security | Between Groups | 3.259 | 2 | 1.630 | 1.493 | .229 |
| | Within Groups | 126.590 | 116 | 1.091 | | |
| | Total | 129.849 | 118 | | | |
| Reviews | Between Groups | 1.780 | 2 | .890 | .598 | .551 |
| | Within Groups | 172.573 | 116 | 1.488 | | |
| | Total | 174.353 | 118 | | | |
| Trust | Between Groups | 2.561 | 2 | 1.280 | .928 | .398 |
| | Within Groups | 160.078 | 116 | 1.380 | | |
| | Total | 162.639 | 118 | | | |
| Frequency | Between Groups | 1.416 | 2 | .708 | .730 | .484 |
| | Within Groups | 112.550 | 116 | .970 | | |
| | Total | 113.966 | 118 | | | |
| Variety | Between Groups | 4.966 | 2 | 2.483 | 1.735 | .181 |
| | Within Groups | 166.025 | 116 | 1.431 | | |
| | Total | 170.992 | 118 | | | |
| Importance | Between Groups | 2.694 | 2 | 1.347 | .999 | .371 |
| | Within Groups | 156.415 | 116 | 1.348 | | |
| | Total | 159.109 | 118 | | | |
| Pricing | Between Groups | 6.392 | 2 | 3.196 | 2.518 | .085 |
| | Within Groups | 147.255 | 116 | 1.269 | | |
| | Total | 153.647 | 118 | | | |
| Offers | Between Groups | 1.319 | 2 | .660 | .724 | .487 |
| | Within Groups | 105.605 | 116 | .910 | | |
| | Total | 106.924 | 118 | | | |
| Convenience | Between Groups | 5.597 | 2 | 2.799 | 2.302 | .105 |
| | Within Groups | 141.041 | 116 | 1.216 | | |
| | Total | 146.639 | 118 | | | |
| Delivery | Between Groups | 2.291 | 2 | 1.146 | 1.061 | .349 |
| | Within Groups | 125.205 | 116 | 1.079 | | |
| | Total | 127.496 | 118 | | | |
| Timesaving | Between Groups | 7.458 | 2 | 3.729 | 2.803 | .065 |
| | Within Groups | 154.290 | 116 | 1.330 | | |
| | Total | 161.748 | 118 | | | |
| Satisfaction | Between Groups | .657 | 2 | .328 | .312 | .732 |
| | Within Groups | 121.898 | 116 | 1.051 | | |
| | Total | 122.555 | 118 | | | |
| Repurchase | Between Groups | 3.030 | 2 | 1.515 | 1.241 | .293 |
| | Within Groups | 141.609 | 116 | 1.221 | | |
| | Total | 144.639 | 118 | | | |
| Recommend | Between Groups | 3.959 | 2 | 1.979 | 1.614 | .204 |
| | Within Groups | 142.260 | 116 | 1.226 | | |
| | Total | 146.218 | 118 | | | |
| Loyalty | Between Groups | 4.593 | 2 | 2.296 | 1.945 | .148 |

| | | | | | | |
|---|---|---|---|---|---|---|
| | Within Groups | 136.987 | 116 | 1.181 | | |
| | Total | 141.580 | 118 | | | |
| Device | Between Groups | 4.288 | 2 | 2.144 | 1.510 | .225 |
| | Within Groups | 164.703 | 116 | 1.420 | | |
| | Total | 168.992 | 118 | | | |

This ANOVA table presents an analysis of variance across different gender groups concerning various online shopping factors. The "Sum of Squares" reflects the variation due to gender, the "df" (degrees of freedom) shows the number of groups minus one, and the F-value represents the variance ratio between gender groups versus within them. The "Sig." (significance level) column reveals if these gender-based differences are statistically significant.

Most factors, such as "Platform" (p = .726), "Products" (p = .469), "Spend" (p = .397), "Security" (p = .229), "Trust" (p = .398), "Frequency" (p = .484), "Variety" (p = .181), "Importance" (p = .371), and "Offers" (p = .487), show p-values above .05, indicating no statistically significant difference between gender groups. This suggests that men, women, and other genders view these aspects similarly when it comes to online shopping. For example, preferences regarding platform choice, trust, and variety do not significantly vary across gender groups, implying a broadly similar experience. While some factors, such as "Pricing" (p = .085), "Convenience" (p = .105), "Timesaving" (p = .065), and "Loyalty" (p = .148), display p-values slightly below .10, they still do not meet the strict p < .05 threshold, though they could indicate a potential trend worth further exploration. These near-significance levels suggest that gender may somewhat influence perspectives on pricing, time-saving benefits, and loyalty, albeit not strongly enough to be conclusive.

In summary, the analysis indicates that gender does not lead to major differences in how most factors related to online shopping are perceived. This outcome can inform marketers that targeting online shopping experiences based on gender might not be necessary, as the core factors are perceived uniformly across genders.

**Table 9. ANOVA between Education and Factors**

| | | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|
| Platform | Between Groups | 28.544 | 4 | 7.136 | 3.756 | .007 |
| | Within Groups | 216.615 | 114 | 1.900 | | |
| | Total | 245.160 | 118 | | | |
| Products | Between Groups | 34.186 | 4 | 8.546 | 4.180 | .003 |
| | Within Groups | 233.091 | 114 | 2.045 | | |
| | Total | 267.277 | 118 | | | |
| Spend | Between Groups | 9.457 | 4 | 2.364 | 1.773 | .139 |
| | Within Groups | 152.038 | 114 | 1.334 | | |
| | Total | 161.496 | 118 | | | |
| Security | Between Groups | 14.156 | 4 | 3.539 | 3.487 | .010 |
| | Within Groups | 115.692 | 114 | 1.015 | | |
| | Total | 129.849 | 118 | | | |
| Reviews | Between Groups | 19.300 | 4 | 4.825 | 3.548 | .009 |
| | Within Groups | 155.053 | 114 | 1.360 | | |
| | Total | 174.353 | 118 | | | |
| Trust | Between Groups | 17.265 | 4 | 4.316 | 3.385 | .012 |
| | Within Groups | 145.373 | 114 | 1.275 | | |

| | | | | | | |
|---|---|---|---|---|---|---|
| | Total | 162.639 | 118 | | | |
| Frequency | Between Groups | 3.272 | 4 | .818 | .843 | .501 |
| | Within Groups | 110.694 | 114 | .971 | | |
| | Total | 113.966 | 118 | | | |
| Variety | Between Groups | 11.182 | 4 | 2.796 | 1.994 | .100 |
| | Within Groups | 159.809 | 114 | 1.402 | | |
| | Total | 170.992 | 118 | | | |
| Importance | Between Groups | 6.558 | 4 | 1.639 | 1.225 | .304 |
| | Within Groups | 152.551 | 114 | 1.338 | | |
| | Total | 159.109 | 118 | | | |
| Pricing | Between Groups | 11.197 | 4 | 2.799 | 2.240 | .069 |
| | Within Groups | 142.450 | 114 | 1.250 | | |
| | Total | 153.647 | 118 | | | |
| Offers | Between Groups | 1.705 | 4 | .426 | .462 | .764 |
| | Within Groups | 105.220 | 114 | .923 | | |
| | Total | 106.924 | 118 | | | |
| Convenience | Between Groups | 5.376 | 4 | 1.344 | 1.085 | .368 |
| | Within Groups | 141.263 | 114 | 1.239 | | |
| | Total | 146.639 | 118 | | | |
| Delivery | Between Groups | 5.969 | 4 | 1.492 | 1.400 | .239 |
| | Within Groups | 121.527 | 114 | 1.066 | | |
| | Total | 127.496 | 118 | | | |
| Timesaving | Between Groups | 3.562 | 4 | .891 | .642 | .634 |
| | Within Groups | 158.186 | 114 | 1.388 | | |
| | Total | 161.748 | 118 | | | |
| Satisfaction | Between Groups | 6.394 | 4 | 1.599 | 1.569 | .187 |
| | Within Groups | 116.160 | 114 | 1.019 | | |
| | Total | 122.555 | 118 | | | |
| Repurchase | Between Groups | 5.478 | 4 | 1.370 | 1.122 | .350 |
| | Within Groups | 139.160 | 114 | 1.221 | | |
| | Total | 144.639 | 118 | | | |
| Recommend | Between Groups | 8.251 | 4 | 2.063 | 1.704 | .154 |
| | Within Groups | 137.968 | 114 | 1.210 | | |
| | Total | 146.218 | 118 | | | |
| Loyalty | Between Groups | 8.638 | 4 | 2.159 | 1.852 | .124 |
| | Within Groups | 132.942 | 114 | 1.166 | | |
| | Total | 141.580 | 118 | | | |
| Device | Between Groups | 16.567 | 4 | 4.142 | 3.098 | .018 |
| | Within Groups | 152.425 | 114 | 1.337 | | |
| | Total | 168.992 | 118 | | | |

This ANOVA table examines differences in perceptions of various online shopping factors based on education level. A significant F-value ($p < .05$) suggests that education level impacts how participants view that specific factor.

The "Platform" factor shows a significant difference ($p = .007$), indicating that platform preferences vary by education. Similarly, "Products" ($p = .003$) reveals that different educational backgrounds influence product preferences. "Security" ($p = .010$) also shows variation, suggesting differing levels of concern for secure transactions based on education. For "Reviews" ($p = .009$) and "Trust" ($p = .012$), educational background plays a significant role, with higher education likely correlating with a greater reliance on reviews and trust in platforms. Finally, the "Device" factor ($p = .018$) reveals that preferred devices for online shopping vary by education level, possibly due to differences in tech accessibility or preference across educational backgrounds.

Other factors, such as "Spend" ($p = .139$), "Variety" ($p = .100$), "Pricing" ($p = .069$), "Convenience" ($p = .368$), "Delivery" ($p = .239$), and "Loyalty" ($p = .124$), show no significant differences ($p > .05$), indicating that educational background does not largely affect views on spending habits, pricing, convenience, or loyalty. Factors such as "Timesaving" ($p = .634$), "Satisfaction" ($p = .187$), "Repurchase" ($p = .350$), and "Recommend" ($p = .154$) are also not significantly influenced by education level.

In summary, education level significantly impacts preferences on certain aspects, such as platform choice, security concerns, product preferences, and device usage, while other areas of online shopping are perceived similarly across educational backgrounds. This suggests that tailoring marketing strategies based on educational demographics could be useful in areas of platform selection, security, and device optimization.

## CONCLUSION

The study provides valuable insights into how demographics, particularly age, gender, and education level, impact perceptions and preferences regarding various factors of online shopping, including platform choice, product selection, security, trust, and device usage. Through a structured analysis using ANOVA, this research highlights that certain factors, like platform preference, security concerns, and reliance on reviews, show significant variation based on demographics. This reveals that online shopping experiences and motivations are diverse and shaped by demographic distinctions, emphasizing the importance for e-commerce platforms to consider these differences when designing their user experiences and marketing strategies.

For instance, age differences significantly impact preferences for online shopping platforms and the importance placed on product variety and trust in security measures. Younger users, particularly in the 18-25 demographic, demonstrate higher engagement with online shopping, influenced by factors such as convenience and variety, whereas older groups show comparatively lower levels of interaction. Education also plays a role, with higher-educated users displaying a greater reliance on reviews and security in their decision-making processes. These findings underscore the necessity for e-commerce platforms to tailor features like product recommendations, payment security, and review visibility to align with varied consumer needs.

Future research can expand on this by exploring the psychological and behavioral motivations behind these demographic-based preferences. Additionally, longitudinal studies may examine how these preferences evolve over time with advancing technology and changing consumer behaviors. Research on the impact of cultural factors on online shopping behavior across different countries would offer a broader perspective, allowing for a more globally relevant understanding of e-commerce trends.

The global implications of these findings are significant. As e-commerce continues to grow internationally, particularly in emerging markets, understanding demographic influences on shopping behavior can help businesses cater to diverse customer bases more effectively. This can lead to higher user satisfaction, increased customer retention, and ultimately, enhanced global market penetration. By prioritizing data-driven, demographically informed strategies, e-commerce platforms can not only improve customer experience but also contribute to the sustainable growth of the global digital economy, bridging consumer needs with technological advancements across different cultures and age groups.

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