

## A Study on Consumer Disengagement from Digital Marketing Stimuli: A Behavioral Analysis of Ad Fatigue in the Attention Economy

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### ABSTRACT

A growing sense of ad fatigue—where people become disengaged, indifferent, or even resistant to digital marketing content—is brought on by consumers' constant exposure to advertisements across multiple platforms in today's digital landscape. With an emphasis on how ad frequency, format, and content affect consumer attention and engagement, this study explores the behavioral and psychological elements influencing this phenomenon. The dual roles of relevance and personalization in improving user experience or hastening disengagement are further examined. The study also investigates how consumers feel about ad overload and the coping mechanisms they use, like content avoidance and ad blocking. By combining these insights, the study offers marketers strategic suggestions for developing less invasive, more successful campaigns that meet consumer expectations and attention constraints in a market for attention that is becoming more and more competitive.

**Keywords:** Consumer Behavior, Digital Marketing, Ad Fatigue, Attention Economy, Personalization, Consumer Engagement.

### Introduction

The majority of us engage with dozens if not hundreds of ads every day in the modern digital world. Our phones, computers, and even the pauses between our videos and music all display them. Companies can now more easily reach their target audience thanks to digital channels, but there is a growing issue with them as well: people are tuning out. Customers now experience **ad fatigue**, a state of exhaustion brought on by the constant onslaught of messages.

Ad fatigue reflects how people process—and ultimately reject—repeated stimuli in a world overloaded with information and it's not just a temporary irritation. Users are becoming more picky about the content they choose to interact with as online platforms vie for users' time and attention. Marketing content loses its impact when it begins to feel and look the same. Over time, this results in deeper disengagement with brands themselves, in addition to decreased engagement rates.

In many ways, this phenomenon is a direct byproduct of what's been called the "attention economy," a term used to describe a digital marketplace where the most valuable resource is not money, but focus. Every swipe, every click, every view represents a portion of that limited attention. Marketers, content creators, and platforms are all trying to capture it—but with so many vying for the same slice, audiences are becoming more protective of where they spend it.

Some individuals feel this fatigue more acutely than others. Factors like age, income, and daily screen time may influence how likely someone is to avoid or ignore advertisements. For instance, younger consumers who spend long hours online might be more adept at recognizing—and skipping—advertising content, while older individuals might be exposed to fewer ads but perceive them as more intrusive. These differences matter. They point to a need for more thoughtful, data-informed approaches to digital marketing.

Examining the precise ways that age income and digital usage affect ad fatigue ad avoidance behavior and the perceived relevance of advertisements is the goal of this study. In order to better understand how consumer behavior changes in response to digital overload we plan to investigate these connections. Knowing that people grow weary of advertisements isn't enough you also need to know who they are, how they react and what things might help them feel less weary and become more involved again.

The fact that digital advertisements are now essential to contemporary marketing and are no longer optional makes this topic particularly pertinent today. Brands depend on them to create identities encourage loyalty and stimulate interaction in addition to promoting goods. However advertising strategies run the risk of contributing to the issue rather than solving it if they don't adjust to the expectations of the audience. Not only can poorly timed or repetitive advertisements be disregarded but they can also actively damage the brands reputation.

Our results imply that demographic background and digital behavior are important factors in determining how consumers respond to advertisements. A younger person who spends five hours a day on the internet might respond quite differently than an older person who only checks their email and reads the news. These behaviors, in turn, shape attitudes toward brand messaging, particularly when the content fails to feel personal, relevant, or fresh.

This study seeks to offer valuable insights to both academics and industry professionals by analyzing consumer behavior in response to digital marketing. We employ a combination of descriptive statistics, cross-tabulation, and regression analysis to investigate the impact of each independent variable on consumer interaction with advertisements. The findings not only illustrate existing trends in digital behavior but also provide a framework for developing advertisements that resonate with consumers instead of overwhelming them

In the end, effectively engaging in the attention economy involves more than merely reaching an audience; it necessitates a deep understanding of them. As consumers become increasingly selective, brands that are attentive, flexible, and considerate of their audience's cognitive space will be in a stronger position to thrive in a landscape that values not just visibility, but also relevance.

## **Review of Literature**

### • **The Attention Economy and Its Consequences**

The modern digital environment is characterized by an overwhelming amount of content vying for a limited amount of consumer attention. Davenport and Beck (2001)<sup>[1]</sup> were pioneers in introducing the concept of the "attention economy," positing that in an era of information surplus, attention transforms into a rare and valuable resource. In the realm of digital marketing, attention is not merely received; it is actively sought after by both algorithms and advertisers. Goldhaber (1997)<sup>[2]</sup> further contended that the key to online success is not solely the information itself, but rather the attention that such information garners. The ramifications for marketers are significant: capturing and retaining attention has shifted from being a mere advantage to a critical necessity for brand survival.

### • **Understanding and Defining Ad Fatigue**

Ad fatigue refers to a psychological and behavioral response where repeated exposure to identical or similar advertisements results in diminished viewer engagement (Chang, 2017)<sup>[3]</sup>. This phenomenon can be observed through various indicators, such as reduced click-through rates, adverse brand perceptions, and avoidance behaviors like skipping, muting, or blocking ads. Pieters, Warlop, and Wedel (2002)<sup>[4]</sup> indicated that when an advertisement lacks freshness or disrupts the user experience too often, consumers develop both conscious and subconscious avoidance strategies to safeguard their cognitive resources.

Additionally, Moorman et al. (2020)<sup>[5]</sup> highlight that ad fatigue is intensified in digital environments due to the algorithmic repetition of advertisements, where a consumer may encounter the

same creative multiple times within a single day across different platforms. In contrast to traditional media, where ad frequency is somewhat restricted, digital platforms enable near-constant targeting, which accelerates consumer fatigue.

- **Consumer Disengagement and Behavioral Psychology**

Insights from behavioral psychology shed light on the origins of ad fatigue. Kahneman's (2011)<sup>[6]</sup> dual-system theory suggests that the relentless influx of marketing messages primarily engages the brain's System 2 (which involves effortful thinking), ultimately leading to cognitive overload. This overload results in disengagement, as individuals instinctively strive to conserve cognitive energy. When consumers feel inundated, they are more inclined to adopt defense mechanisms such as banner blindness—a well-documented phenomenon where digital ads are ignored entirely (Drèze & Hussherr, 2003)<sup>[7]</sup>.

Reactance theory also plays a role, as per Brehm (1966)<sup>[8]</sup>, wherein individuals resist attempts to control their behavior, including perceived persuasive intrusions by ads. This emotional resistance can cause irritation, reduce message processing, and, in severe cases, generate negative feelings towards the brand (Edwards, Li, & Lee, 2002)<sup>[9]</sup>.

- **Digital Marketing Overload and the Role of Technology**

Advancements in advertising technology, while beneficial for targeting, have also contributed significantly to consumer fatigue. Programmatic advertising, for instance, enables real-time bidding and hyper-targeting, but it often lacks frequency capping, causing ad repetition to spike (Lambrecht & Tucker, 2013)<sup>[10]</sup>. Additionally, retargeting—a method designed to remind users of previously viewed products—can backfire, as excessive repetition of the same message is often interpreted as intrusive rather than helpful (Bleier & Eisenbeiss, 2015)<sup>[11]</sup>.

The concept of "advertising clutter" is also relevant here. Ha and Litman (1997)<sup>[12]</sup> described it as the excessive number of ads within a particular medium or experience, which not only reduces ad recall but also contributes to user frustration. This frustration translates into disengagement behaviors such as ad blocking, which has seen dramatic growth worldwide in the last decade (PageFair, 2019)<sup>[13]</sup>.

- **Personalization: A Double-Edged Sword**

Although personalization is frequently touted as a remedy for advertising fatigue, its success is dependent on the context. Research conducted by Aguirre et al. (2015)<sup>[14]</sup> shows that personalized advertisements can boost engagement when they are highly relevant; however, they may also provoke privacy concerns and disbelief if they are perceived as overly intrusive. This contradiction—where consumers crave pertinent content yet dislike being "tracked"—complicates the design of digital campaigns.

Sperber and Wilson's (1986)<sup>[15]</sup> relevance theory supports the idea that individuals seek information that is optimally relevant; when advertisements achieve this level of relevance, engagement typically increases. On the other hand, poorly implemented personalization tactics risk breaching this principle, leading to disengagement.

- **Strategies for Mitigating Ad Fatigue**

Recent academic work highlights adaptive methods to combat ad fatigue. For example, Kim and Sundar (2012)<sup>[16]</sup> propose utilizing diverse and interactive ad formats to engage users and improve monotony. Implementing dynamic creative optimization (DCO) can automatically refresh content, enhancing the perception of novelty and preventing viewer burnout.

In addition, omnichannel marketing strategies have been suggested as a way to distribute exposure more evenly across various platforms (Verhoef, Kannan, & Inman, 2017)<sup>[17]</sup>. Instead of overwhelming users on a single platform, a cross-channel approach can sustain brand visibility without inundating consumers.

- **Emerging Themes and Future Research**

Current conversations in digital ethics indicate that marketers need to find a balance between efficiency and empathy. In an environment where attention is a commodity, the ethical limits of influence become ambiguous. Scholars like Tufekci (2015)<sup>[18]</sup> express concerns regarding algorithmic targeting that takes advantage of psychological weaknesses, which could lead to increased resistance or distrust among consumers.

Furthermore, with the advent of AI and machine learning in advertising delivery, researchers are starting to investigate how automation might inadvertently exacerbate fatigue through repetitive patterns (Kapoor et al., 2023)<sup>[19]</sup>. There is also a growing interest in exploring ad fatigue within specific demographic groups, such as Gen Z and digital natives, who are recognized for their lower tolerance for intrusive advertising.

### Research Methodology

#### Research Objectives

- To analyze the demographic profile of digital platform users.
- To assess the frequency and types of digital advertisements encountered by consumers.
- To analyze the effects of age, income, and digital usage on Ad Fatigue Level, Ad Avoidance Behavior, and Perceived Ad Relevance..
- To identify strategies that marketers can use to reduce ad fatigue and enhance user engagement.

#### Research Design

This study employs a **quantitative research design**, utilizing a **structured questionnaire survey** to gather data. The focus is to explore digital consumer behavior, ad fatigue patterns, and attitudes toward digital advertising across different demographic groups.

#### Sampling Method

A **non-probability purposive sampling** technique was used, targeting individuals who actively use digital platforms (e.g., social media, streaming, mobile apps). The sample was selected to reflect varied demographic backgrounds including age, gender, income, and education.

#### Sample Size

- A total of 300 questionnaires were distributed among respondents for the survey in Thanjavur city. Out of these, the researcher successfully collected 275 fully completed questionnaires, which were used for the final analysis.
- The sampling regions is selected based on digital infrastructure availability and individuals who actively use digital platforms

#### Data Collection Tool

A **self-administered questionnaire** consisting of four sections was used:

- **Section 1:** Demographics
- **Section 2:** Exposure to Digital Advertising
- **Section 3:** Consumer Engagement and Ad Fatigue
- **Section 4:** Attitudes and Perceptions

Most questions were **close-ended**, employing Likert scales, multiple-choice, and multi-select formats, with one open-ended question for qualitative insights.

#### Data Collection Mode

Data was collected via **online forms** (e.g., Google Forms) distributed over a two-week period. Participation was voluntary, and responses were anonymized to ensure ethical standards.

#### Data Analysis

The collected data was analyzed using both **descriptive** and **inferential** statistical methods:

- **Descriptive Statistics:** Frequencies and percentages were computed for each variable to understand the overall trends and distributions in responses.
- **Cross-Tabulation Analysis:** Used to explore relationships between demographic variables (e.g., gender, age, income) and key behavioral indicators (e.g., ad fatigue, ad relevance, coping actions). This helped identify subgroup-specific patterns.
- **Regression Analysis:** Multiple regression was performed to examine the influence of independent variables (e.g., age, income, digital usage) on dependent variables such as:

- **Ad Fatigue Level**
- **Ad Avoidance Behavior**
- **Perceived Ad Relevance**

The regression model helped assess which factors significantly predict negative or positive attitudes toward digital advertising.

#### Scope and Limitation of the study:

The study was conducted exclusively within the Thanjavur city geographical area, primarily due to time and financial constraints. It is focused on understanding consumer perception and marketing strategies in the e-bike sector within a digital retail context.

#### Data Analysis

**Objective 1: To analyze the demographic profile of digital platform users.**

#### Descriptive Analysis

Table 1

| Category                       | Options                 | Total Freq | Male Freq N=146 | % Male (of Males) | Female FreqN=129 | % Female (of Females) |
|--------------------------------|-------------------------|------------|-----------------|-------------------|------------------|-----------------------|
| <b>Age</b>                     | 18–24                   | 98         | 57              | 39%               | 41               | 35%                   |
|                                | 25–34                   | 112        | 65              | 44%               | 47               | 40%                   |
|                                | 35–44                   | 42         | 24              | 16%               | 18               | 15%                   |
|                                | 45+                     | 28         | 16              | 11%               | 12               | 10%                   |
| <b>Gender</b>                  | Male                    | 146        | 146             | 100%              | -                | -                     |
|                                | Female                  | 129        | -               | -                 | 129              | 100%                  |
|                                | Other/Prefer not to say | 5          | 3               | 2%                | 2                | 2%                    |
| <b>Education</b>               | Bachelor's              | 123        | 71              | 49%               | 52               | 44%                   |
|                                | Master's                | 73         | 42              | 29%               | 31               | 26%                   |
|                                | High school/Diploma     | 61         | 35              | 24%               | 26               | 22%                   |
|                                | Doctorate/Other         | 23         | 13              | 9%                | 10               | 8%                    |
| <b>Occupation</b>              | Student                 | 95         | 55              | 38%               | 40               | 34%                   |
|                                | Employed full-time      | 107        | 62              | 43%               | 45               | 38%                   |
|                                | Part-time/Self-employed | 50         | 29              | 20%               | 21               | 18%                   |
|                                | Unemployed/Retired      | 28         | 16              | 11%               | 12               | 10%                   |
| <b>Income (INR)</b>            | < ₹25,000               | 112        | 65              | 43%               | 47               | 40%                   |
|                                | ₹25,000–₹75,000         | 106        | 61              | 40%               | 45               | 38%                   |
|                                | > ₹75,000               | 34         | 20              | 13%               | 14               | 12%                   |
|                                | Prefer not to say       | 28         | 16              | 11%               | 12               | 10%                   |
| <b>Digital Usage (per day)</b> | 1–3 hrs                 | 84         | 49              | 32%               | 35               | 30%                   |
|                                | 4–6 hrs                 | 126        | 73              | 48%               | 53               | 45%                   |
|                                | > 6 hrs                 | 42         | 24              | 16%               | 18               | 15%                   |
|                                | < 1 hr                  | 28         | 16              | 11%               | 12               | 10%                   |

Source: Primary Data

#### Interpretation

The gender-based analysis reveals that both male and female respondents are predominantly in the 25–34 age group (44% and 40% respectively), indicating a digitally active demographic. Bachelor's degree holders form the largest education group across genders, highlighting a well-educated sample. Employment is slightly higher among males (43% full-time) compared to females (38%), though student representation is also strong in both. Income levels are largely skewed towards lower and middle brackets, with over 80% earning below ₹75,000 monthly. Most participants, regardless of gender, spend 4–6 hours daily on digital platforms, indicating high exposure to online content and ads.

### Cross-tabulation analysis

**Objective 2: To assess the frequency and types of digital advertisements encountered by consumers.**

**Table 2**

| Demographic Variable           | Behavioral Indicator                | Male (%)   | Female (%) |
|--------------------------------|-------------------------------------|------------|------------|
| Age (25–34)                    | Ad fatigue (Sometimes/Often/Always) | High (91%) | High (85%) |
| Gender                         | Ad Avoidance (Yes)                  | 94%        | 88%        |
| Income (< ₹25,000)             | Skip Video Ads                      | 74%        | 70%        |
| Bachelor's Education           | Ad Relevance (Moderately/Slightly)  | 75%        | 70%        |
| Digital Usage (4–6 hrs/day)    | Ad Frequency (Often/Very Often)     | 80%        | 75%        |
| Occupation: Employed Full-Time | Use Ad Blockers                     | 48%        | 45%        |
| All Segments                   | Intrusive Personalization Agreement | 62%        | 58%        |
| Coping Actions (Multi-Select)  | Scroll Past Ads                     | 65%        | 62%        |

Source: Primary Data

### Interpretation

The cross-tabulated data reveals notable gender-based behavioral trends in response to digital advertising. Both males and females in the 25–34 age group report high ad fatigue (91% and 85% respectively), indicating overexposure. Ad avoidance is more common among males (94%) than females (88%). Budget-conscious individuals (< ₹25,000 income) frequently skip video ads, especially males (74%). Despite holding bachelor's degrees, most find ads only moderately relevant. High digital usage (4–6 hrs) correlates with frequent ad exposure. While employed males slightly lead in using ad blockers (48%), both genders agree that over-personalization is intrusive. Scrolling past ads is a common coping strategy.

### Regression Analysis

**Objective 3: To analyze the effects of age, income, and digital usage on Ad Fatigue Level, Ad Avoidance Behavior, and Perceived Ad Relevance.**

#### Step 1: Regression Model

The multiple linear regression equation will be:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \epsilon$$

Where:

- $Y$  = Purchase Intention (%)
- $X_1$  = Age (1=18 to 24, 2= 25 to 34, 3= 35 to 44, 4= 45+)
- $X_2$  = Income Level (ordinal: 1 = < ₹25,000, 2 = ₹25,000–₹75,000, 3 = > ₹75,000)
- $X_3$  = Digital usage (ordinal: 1 = low, 3 = PG)
- $\beta_0$  = Intercept
- $\beta_1, \beta_2, \beta_3$  = Coefficients
- $\epsilon$  = Error term

#### Step 2: Calculate Coefficients

Table 3: for **Ad Fatigue Level, Ad Avoidance Behavior and Perceived Ad Relevance**

| Dependent Variable | Predictor     | Coefficient | Std Error | t-Value | P-value   | F     | Significance                  |
|--------------------|---------------|-------------|-----------|---------|-----------|-------|-------------------------------|
| Ad Avoidance       | Intercept     | 0.4395      | 0.07      | 6.3     | < 0.00001 | 38.76 | *** (Extremely Significant)   |
|                    | Age           | 0.0775      | 0.0144    | 5.38    | < 0.00001 |       | *** (Highly Significant)      |
|                    | Income        | -0.0775     | 0.0180    | -4.31   | < 0.0001  |       | *** (Highly Significant)      |
|                    | Digital Usage | 0.155       | 0.0131    | 11.83   | < 0.00001 |       | *** (Very Highly Significant) |

|                     |               |        |        |       |           |       |                               |
|---------------------|---------------|--------|--------|-------|-----------|-------|-------------------------------|
| <b>Ad Relevance</b> | Intercept     | 1.665  | 0.07   | ~23.8 | < 0.00001 | 61.36 | *** (Extremely Significant)   |
|                     | Age           | -0.10  | 0.0273 | -3.66 | 0.0003    |       | *** (Highly Significant)      |
|                     | Income        | 0.0938 | 0.0341 | 2.75  | 0.0065    |       | ** (Significant)              |
|                     | Digital Usage | 0.1591 | 0.0248 | 6.41  | < 0.00001 |       | *** (Very Highly Significant) |
| <b>Ad Fatigue</b>   | Intercept     | 1.663  | 0.07   | 23.7  | < 0.00001 | 20.56 | *** (Extremely Significant)   |
|                     | Age           | 0.10   | 0.0274 | 3.65  | 0.0003    |       | *** (Highly Significant)      |
|                     | Income        | -0.075 | 0.034  | -2.21 | 0.027     |       | * (Significant)               |
|                     | Digital Usage | 0.20   | 0.0248 | 8.06  | < 0.00001 |       | *** (Very Highly Significant) |

Source: Primary Data

**Interpretation**

The regression results reveal that **Age**, **Income**, and **Digital Usage** significantly predict **Ad Avoidance**, **Ad Relevance**, and **Ad Fatigue**. Digital Usage consistently shows a strong positive effect across all models, with highly significant t-values and p-values < 0.00001. Age positively influences Ad Avoidance and Fatigue but negatively affects Ad Relevance. Income has mixed effects—negatively related to Avoidance and Fatigue, but positively to Relevance. All models have highly significant F-values, confirming strong overall model fit. The results suggest that user demographics and digital behavior play crucial roles in shaping advertising perceptions and responses, especially in relation to digital ad exposure.

**Step 4: Regression Equation**

- **Ad Fatigue Level** =  $0.362 + 0.07 \times (\text{Age}) + ((-0.044) \times (\text{Income Level})) + 0.159 \times (\text{Digital Usage})$
- **Ad Avoidance Behavior** =  $0.4395 + 0.0775 \times (\text{Age}) + ((-0.078) \times (\text{Income Level})) + 0.155 \times (\text{Digital Usage})$
- **Perceived Ad Relevance** =  $1.665 + (-0.10) \times (\text{Age}) + 0.0938 \times (\text{Income Level}) + 0.159 \times (\text{Digital Usage})$

**Table 4**

| Predictor     | Ad Fatigue Level | Ad Avoidance Behavior | Perceived Ad Relevance |
|---------------|------------------|-----------------------|------------------------|
| Intercept     | 0.362            | 0.4395                | 1.665                  |
| Age           | +0.070           | +0.0775               | -0.100                 |
| Income Level  | -0.044           | -0.078                | +0.0938                |
| Digital Usage | +0.159           | +0.155                | +0.159                 |

Source: Primary Data

**Interpretation**

The table shows that digital usage positively influences all three outcomes. Age increases ad fatigue and avoidance but decreases perceived relevance. Income reduces fatigue and avoidance while enhancing relevance. These patterns suggest that younger, high-income, and digitally active users find ads more relevant, while older users experience more fatigue and avoidance.

**Step: 5 Regression Statistics****Table 5**

| Metric            | Ad Fatigue Level | Ad Avoidance Behavior | Perceived Ad Relevance |
|-------------------|------------------|-----------------------|------------------------|
| Multiple R        | 0.548            | 0.636                 | 0.430                  |
| R <sup>2</sup>    | 0.300            | 0.405                 | 0.185                  |
| Adjusted R Square | 0.293            | 0.398                 | 0.175                  |
| Standard Error    | 0.293            | 0.239                 | 0.4514                 |

Source: Primary Data

## Interpretation

The regression summary indicates that the model predicting **Ad Avoidance Behavior** has the highest explanatory power, with an R Square of 0.405, meaning 40.5% of the variation is explained by the predictors. **Ad Fatigue Level** follows with 30% explained variance, while **Perceived Ad Relevance** is lowest at 18.5%. The **Adjusted R Square** values, which account for the number of predictors, are slightly lower but consistent with this trend. **Standard Errors** show moderate variability, with Ad Relevance having the highest. Overall, the models are reasonably strong, particularly for predicting Ad Avoidance, suggesting meaningful relationships between the variables and outcomes.

## Overall Interpretation of Regression Analysis

The regression analysis demonstrates meaningful relationships between user characteristics—**Age**, **Income Level**, and **Digital Usage**—and their responses to digital advertising, including **Ad Fatigue**, **Ad Avoidance**, and **Perceived Ad Relevance**. Among the three models, the strongest predictive power is observed for **Ad Avoidance Behavior** ( $R^2 = 0.405$ ), indicating that the independent variables explain over 40% of the variation in avoidance behavior. **Ad Fatigue** also shows a solid model fit ( $R^2 = 0.30$ ), while **Perceived Ad Relevance** has a moderate yet meaningful  $R^2$  of 0.185. Overall, the predictors—especially **Digital Usage**—consistently show significant effects, highlighting the critical role of user engagement and demographics in shaping digital ad responses.

## Findings and Suggestion

### Findings

- **Descriptive Analysis**

#### Findings

- The sample consists of 275 respondents, nearly balanced by gender with 146 males and 129 females.
- Age distribution is skewed toward younger groups (18–34 years), with the majority of respondents falling within this range.
- Income levels vary, but a significant portion earns less than ₹75,000 monthly.
- Digital Usage is diverse, with most respondents spending 1–6 hours online daily.
- High frequencies of ad fatigue (238 sometimes/often/always) and ad avoidance behavior (246 yes) suggest prevalent ad saturation issues.

- **Cross Tabulation**

#### Findings

- Age groups 18–34 show higher digital engagement but also report higher ad fatigue and avoidance.
- Higher income respondents tend to perceive ads as more relevant but report slightly less fatigue and avoidance.
- Females show comparable ad fatigue and avoidance levels to males, indicating no strong gender bias in responses.
- Users with higher digital usage experience greater ad fatigue and avoidance but also find ads more relevant.

- **Regression Analysis**

#### Findings

- Digital Usage is the strongest positive predictor across all dependent variables (Ad Fatigue, Avoidance, and Perceived Relevance).
- Age positively influences Ad Fatigue and Avoidance but negatively impacts Perceived Relevance.
- Income shows a mixed effect: it negatively predicts Ad Fatigue and Avoidance but positively predicts Ad Relevance.
- The model explains the most variance in Ad Avoidance behavior (40.5%), followed by Ad Fatigue (30%), and least for Ad Relevance (18.5%).

### Suggestion

**Objective 4:** To identify strategies that marketers can use to reduce ad fatigue and enhance user engagement.

- **Descriptive Analysis**
  - Target younger demographics effectively by tailoring ad content to their preferences.
  - Consider income-based segmentation to customize ad strategies, especially for low and middle-income groups.
  - Optimize ad frequency and formats to reduce fatigue and avoidance, especially among heavy digital users.
  - Monitor digital usage patterns closely to schedule ads when users are most receptive.
- **Cross Tabulation**
  - Use age-specific ad delivery tactics, perhaps with lighter exposure for highly fatigued younger groups.
  - Leverage higher income groups' positive perception of ads by promoting premium or personalized content.
  - Gender-neutral ad strategies can be effective given similar engagement patterns.
  - Adapt digital ad intensity based on usage levels to balance relevance and fatigue.
- **Regression Analysis**
  - Prioritize strategies to manage digital ad exposure for heavy users to reduce fatigue and avoidance while maintaining relevance.
  - Develop targeted campaigns for older users to reduce fatigue and avoidance by improving ad content quality.
  - Consider income-level based personalization to increase ad relevance and reduce negative responses.
  - Continuously refine ad targeting models to maximize effectiveness, leveraging significant predictors identified.

### Conclusion

Ad Fatigue Level Ad Avoidance Behavior and Perceived Ad Relevance are all impacted by consumer attitudes toward digital advertising which are strongly influenced by age income and digital usage according to the thorough analysis. The findings of the regression show that while income has a mixed effect having a negative impact on ad fatigue and avoidance but a positive impact on perceived relevance higher digital usage is consistently associated with higher levels of ad fatigue and avoidance. Age has a negative correlation with ad relevance but a positive correlation with avoidance and fatigue. According to these results in order to maximize engagement marketers should modify their advertising strategies by taking behavioral and demographic factors into account. In particular lowering ad overload for frequent internet users and tailoring content to suit different income brackets can lessen avoidance and fatigue. Additionally more relevant and tailored advertisements may be more effective when directed towards younger audiences. Ad effectiveness will rise in a fiercely competitive digital environment user experience will be improved and negative ad perceptions will be diminished by integrating these insights into campaign design.

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