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The Effect of Reference Prices Anchoring on Price Perception and Purchase Intent in Online Retail among High School Students: A Secondary-Data Analysis of Reference Price Effects on Willingness to Pay

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Abstract: ***This study investigates the effect of reference price, anchoring on price perception, and willingness to pay (WTP) in online retail stores among high school students through a secondary data research design. Rather than collecting primary data, this study synthesises evidence from published experimental studies on anchoring bias, publicly available, consumer data sets, and archival online retail pricing data to examine how crossed out "original price" influences a consumers' evaluation, and perception of discounted products. A structured literature synthesis is completed by an analysis of real e-commerce listings to compare pricing methods across youth specific products categories, including electronics, apparel, and gaming accessories. Where available age disagreed, consumer survey data are used to strengthen the relevance of the findings to adolescent consumers. The analysis will evaluate the relationship between reference price display, perceived product value, deal, attractiveness, and willingness to pay while considering the modernity influence of product, category and financial literacy. The coherent evidence indicates that high reference prices consistently increase perceived value and willingness to pay by serving as a cognitive anchor, although the magnitude of the effect varies across the context. Defining contribute to behavioural economics research and have implications for consumer protection policy, financial literacy, education, and ethical digital pricing practices aimed at consumers.***

Keywords: Anchoring Bias; Reference Pricing; Willingness to Pay; Online Consumer Behaviour; High School Students

1. Introduction

With the advent of the rapid growth in e-commerce, the ways consumers evaluate products and make purchasing decisions have changed. Unlike traditional shopping, in which consumers can examine physical products before purchase, online shopping is heavily determined by visual and numerical cues displayed through digital interfaces. Therefore, retailers increasingly adopt behavioural pricing strategies intended to influence consumers' perceptions regarding value. One of the most widely used behavioural pricing techniques is reference pricing, which utilises the display of a higher crossed-out 'original' price alongside a lower selling price of the product to show that there is a great discount in order to persuade consumers into making purchases.

Reference pricing takes advantage of the anchoring bias, a type of heuristic[1]. 'Anchoring bias' refers to the reliance of people on the numerical value initially presented in order to make forthcoming judgements. In this case, the reference price in an online retail context serves as an anchor against which consumers evaluate the discounted price, making people's perception of it as more valuable and more saving while influencing willingness to pay (WTP) and purchase intention, even though the reference price may be arbitrarily selected. There is a range of research that proves the effect of anchoring bias on consumer decision-making across retail, financial, and negotiating contexts[2,3,4].

The increased prevalence of smartphones, social media and digital marketplaces has made high school students (aged 14 to 18) an emerging demographic segment of online consumers. Adolescents frequently interact with e-commerce sites while their financial literacy, numeracy skills and decision-making competence are developing[5,6,7]. All the aforementioned characteristics make adolescent consumers increasingly susceptible to behavioural pricing tactics exploiting cognitive biases instead of rational assessments. Although younger consumers demonstrate an ever-increasing purchasing power and importance in commercial activities, most studies concerning anchoring and reference prices have been conducted on adults or university students, leaving limited information about the effect of the same concepts on adolescents.

Thus, this study examines the effect of reference price anchoring on price perception, purchase intention and willingness to pay (WTP) of high school students through the secondary data research approach. Instead of conducting primary research on minors, which will require ethical committee permission, consent of parents and extensive participants' recruitment, the current study will synthesise evidence from several published experiments, publicly available consumer data and retail pricing data. By integrating findings from multiple resources, the study evaluates whether a high crossed-out reference price constantly influences adolescents' perception of product value and purchasing behaviour across categories such as electronics, apparel and gaming accessories.

Accordingly, the study addresses the effect of high crossed-out original reference prices on high school students' price perception, willingness to pay and purchase intention in online retail settings. Additionally, it discusses the extent to which secondary data sets and published studies demonstrate that reference price anchoring influences adolescents' evaluation of online products across different product categories.

Building on established literature in behavioural economics and consumer psychology, the study anticipates that the empirical evidence will show reference price anchoring consistently enhancing perceived value, willingness to pay, and purchase intent among adolescent consumers, although there could be variations in magnitude of these effects depending on the product category and the level of financial literacy of consumers.

The findings advance the body of knowledge in behavioural economics and consumer psychology by integrating the extant literature on reference price anchoring in the context of an under-studied population. In addition, they have practical implications for financial literacy education, ethical digital marketing practices, and consumer policy given that online retailers are resorting to behavioural pricing tactics to influence young consumers' purchasing decisions.

The remainder of this paper is organised as follows. The Literature Review section examines the existing research on anchoring bias, reference pricing, consumer decision-making processes, and adolescent purchasing behaviour. The Methodology section describes the secondary data research approach used in this study, including data sources, selection criteria, data collection, and analysis methods. The Results section contains the findings of the study based on the synthesis of the literature review and archival pricing data. The Discussion section interprets these findings in relation to existing behavioural economics research and takes into account their practical implications. Finally, the conclusion summarises the studies, contribution, limitations, and recommendations for future research.

2. Literature Review

Anchoring Heuristic

Anchoring was first identified by Tversky and Kahneman[1], where they found that exposure to an arbitrary numerical anchor (which could be a randomly spinning wheel) would cause the subsequent numerical judgments of participants to converge on the anchored value. This "anchoring-and-insufficient-adjustment" effect was later elaborated on by Ariely, Loewenstein, and Prelec[2], where the authors, using what they termed as "coherent arbitrariness," proved that arbitrarily chosen anchors (for example, the last digit of a participant's identification number) could cause durable shifts in the participants' willingness to pay for consumer products while maintaining internal consistency in the ranking of preferences for the different types of products.

Anchoring in Real-World Pricing

Building on the work of Northcraft and Neale[4], the bias of anchoring has been demonstrated in real-world settings of property valuation, where both amateur and expert real estate agents have been shown to adjust their property valuations towards an arbitrary listing price, even though both groups claim that the listing price does not play much of a role in their reasoning. This is important in demonstrating that anchoring is mainly non-conscious and cannot be reasoned out.

Contexts of Reference Price Advertising

Another parallel stream of research has looked at "reference price" or "former price" advertising in a direct way in retail advertising. Biswas and Blair[3] show that the context in which a reference price is displayed determines its believability and persuasiveness, where context moderates the extent to which a reference price inflates the value or whether it is discounted by the consumer as being unbelievable. The above empirical evidence forms the foundation of using a crossed out "original price" as a price anchor in an online retail advertisement.

Two interrelated lines of literature inspire the choice of adolescents as a target population in this work. The first is the consumer socialization theory of John [5], which explains how children and adolescents gradually acquire the cognitive schemata needed to interpret marketing strategies and notes that adult-level skepticism of persuasive price strategies does not emerge until late adolescence. In turn, Moore [6] applies the concept of advertising literacy to online marketing strategies: because adolescents lack sufficient cognitive schema to interpret sophisticated online marketing techniques like personalized anchors and displayed strike-through prices, these techniques tend to blend less clearly with the underlying product information than traditional print and broadcast marketing.

The second strand is a neuroscience-based dual systems model by Steinberg [7]. This model posits the development of an early maturing socioemotional system that reacts strongly to cues related to rewards and time urgency prior to the development of a more mature cognitive control system responsible for effortful evaluation of those cues.

Together, this literature suggests that high school students can be regarded as a population for whom anchoring on price may be more pronounced than in adults—a hypothesis this paper's secondary-data design is built to evaluate indirectly, since direct adolescent experimentation is outside its scope.

Literature Gap

Although the impact of anchoring on pricing decisions has been widely studied for adults and students[1, 2, 4], and literature on consumer socialization and development has been established to understand the marketing knowledge and decision-making abilities of adolescents[5, 6, 7], there have been very few studies that connect these two streams of research on anchoring among online shoppers in the high school age group. This study attempts to bridge this gap by using only secondary and archival data sources, namely the Open Anchoring Quest database[9] and archival listings from Amazon India[8] and Flipkart India[10].

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3. Methodology

3.1 Secondary-Data Research Design

The study employs a secondary quantitative design involving the use of experimental and observational evidence related to the concept of reference-price anchoring and price evaluation. Primary surveys, interviews, and experiments were not conducted. The methodology investigats the relationship between reference-price anchoring, price evaluation, willingness to pay (WTP), and consumer behaviour without direct engagement of high school students.

There are two complementary data streams that are going to be analyzed. The first one utilizes the dataset called Open Anchoring Quest (OpAQ)9 which comprises trial-level observations collected from previous anchoring experiments, including task type, effect size, and participant age. Thus, it serves as an evidence of the effect of numerical anchors on pricing judgments. The second uses publicly available Amazon India and Flipkart retail datasets containing original and discounted prices and product-category information; the Amazon dataset also includes ratings and rating counts. These data provide observational evidence of reference price practices in online retail.

Since there are no individual-level demographics included in the retail datasets, they cannot be considered direct evidence of the shopping behavior of high school students. Youth-oriented product categories serve as context market variables in the research, while the experimental age-specific evidence is included in OpAQ. The two streams are annually separately, and then subsequently triangulated.

3.1.1 Data Sources and Data Preparation

The OpAQ dataset[9] from the Open Science Framework includes data on 96 anchoring experiments comprising around 21,359 participants where task type, participant responses, effect size, standard error, and age have been reported. Observation selection criteria included price, willingness-to-pay, and willingness-to-accept tasks with effect sizes and standard errors reported, resulting in 45 observations with 8,045 participants. Random-effects meta-analysis with the DerSimonian–Laird estimator was carried out, along with an exploratory age comparison based on mean age ≤25 years versus >25 years in the study level. A ≤21 year threshold resulted in only three studies, which was too few to allow pooling. The ≤25-year group thus serves as a surrogate for young consumers as opposed to a direct proxy for high school students

Amazon India Sales Dataset[8] consists of 1,465 observations including original price, discounted price, discount percentage, rating, and rating count. The selection criteria included Electronics and Computers & Accessories resulting in 979 observations that were further classified based on low-anchor (<20% discount) and high-anchor (≥20% discount). The initially intended electronics-versus-apparel comparison was abandoned due to inadequate apparel data. The Flipkart dataset had 15,003 observations, of which 14,902 observations had valid prices, and filtering based on seven categories of youth-relevant consumable products resulted in 4,786 observations. These included Chocolates & Sweets, Chips/Namkeen & Snacks, Soft Drinks, Juices, Deos/Perfumes & Talc, Creams/Lotions & Skin Care, and Hair Care. Since Flipkart lacked rating and review-count variables, it was used only for descriptive discount analysis, while Amazon was used for demand-proxy tests

3.1.2 Amazon India Dataset

The Amazon India Sales Dataset includes 1,465 product listings, featuring variables like actual_price, discounted_price, discount, product_rating, and rating_count.

The dataset is limited to the Electronics and Computers & Accessories top-level categories, leaving us with 979 product listings. The reason for choosing these categories is their likelihood to be the relevant youth purchase, as these include chargers, cables, earbuds, and other digital accessories. The dataset lacks sufficient apparel and game product listings, preventing me from proceeding with the originally intended electronics versus apparel analysis.

The price fields were scrubbed by removing currency symbols and thousands separators and then being converted to the numeric type. The discount depth was calculated using the discount_percentage field from the dataset. Listings were grouped into the following groups:
Low anchor: discount < 20%
High anchor: discount ≥ 20%

This boundary value corresponds to the pre-defined criteria of the research design.

3.1.3 Flipkart Dataset

The Flipkart dataset consists of 15,003 records. Filtering the data for products with valid MRP > 0 and valid sale price leaves us with 14,902 product listings.

It turns out that most of the product listings belong to the fast-moving consumer goods category rather than apparel and electronics originally anticipated. It was therefore repurposed as a complementary everyday-consumables category, representing products that may plausibly be purchased by younger consumers, such as snacks, drinks, and personal-care products.

Seven youth-relevant categories were retained:
1) Chocolates & Sweets
2) Chips/Namkeen & Snacks
3) Soft Drinks
4) Juices
5) Deos/Perfumes & Talc
6) Creams/Lotions & Skin Care
7) Hair Care

This produced **4,786 listings**. Because the dataset does not contain ratings or review counts, it is used for descriptive analysis of reference-price and discount patterns rather than for the demand-proxy inferential tests conducted on the Amazon data.

3.2.3 Product category selection

Because consumer age is unavailable in the retail datasets, product categories are used as youth-market proxies rather than demographic identifiers. Two broad categories are examined:

Code	Category	Example	Rationale
CAT-A	Consumer personal electronics	Wireless earbuds, gaming headsets, smartwatches	High relevance to younger digital consumers and substantial price variation
CAT-B	Apparel and casual fashion	Casual fashion, Graphic hoodies, athletic sneakers	Products influenced by brand image, aesthetics, and perceived discounts

For Flipkart, the seven categories listed above are grouped as **everyday consumables**. The Flipkart data provide contextual evidence of discounting practices but are not included in the inferential demand analysis because of the absence of rating and review variables.

The original electronics-versus-apparel comparison was therefore replaced with an **Electronics-versus-Computers & Accessories** comparison based on the categories actually available in the Amazon dataset.

3.3 Product Groups and Variables

Considering that there is no information about consumers' age groups within the retail dataset, product categories will be used as proxies for the young market segment instead of being used as demographic variables. Products of Amazon are divided into two groups, namely, Electronics (such as earbuds, chargers, cables) and Computers & Accessories.

The key independent variable for the archival analysis will be the reference-price discount depth, which is computed using the following formula:

$$Dr = \frac{Panchor - Psale}{Panchor}$$

Where Panchor is the original or referenced price and Psale is the reduced price. The bigger Dr indicates a larger displayed price differential. For Amazon, the dataset's reported discount percentage is used directly.

Importantly, Dr is a measure of the magnitude of the discount and not whether there was an anchor presented. In the case of Amazon and Flipkart databases, there is no unanchored control group and therefore we cannot establish the causal effect of presenting the reference price.

The main dependent variable of the observational part is the demand proxy, which is based on reviews. If they are present, the transformation will be:

Demand Proxy= ln(Reviews+1)

This will lower the weight of popular items. Ratings will also be included as additional descriptive measures. These variables represent consumer engagement rather than direct measures of perceived value, willingness to pay (WPT) or purchase intention.

3.4 Statistical Analysis

3.4.1 Data on OpAQ Experimental Anchoring

Observations concerning OpAQ price anchoring were first analyzed through descriptive statistics showing sample size, mean anchoring effect, and variation. A meta-analysis of the 45 trials eligible for inclusion in the research was carried out based on a random effects model applying the DerSimonian-Laird estimator. Effect size, its 95% confidence interval, and level of heterogeneity (I-squared) were estimated. Application of the random-effects approach was justified by the presence of differences between included studies in regard to their samples, products, anchors, and experimental design. An exploratory subgroup analysis by age was made by classifying studies as having the mean age of participants equal to or below 25 and above 25 years. Using a criterion of ≤21 years included only three studies

3.5.2 Archival Retail Data

Descriptive statistics were calculated for anchor price, sale price, discount percentage, star rating, rating count, and product category. The Amazon listing products were grouped as having low anchor price ($D\_r < 0.20$) or high anchor price ($D\_r \geq 0.20$). Welch's independent-samples t-test was used to compare the two groups on star rating and transformed rating count. Since there are reference price products in both groups, the tests examine the relationship between discount level and consumer interest and not causality because of anchoring. Two way analysis of variance was also conducted to examine if there was any difference in the relationship between anchor group and star rating for different product categories of Electronics and Computers & Accessories. The interaction term checks if there is an interaction effect between discount percentage and star rating for the two types of products

3.4.3 Regression Analysis

An OLS regression provides a complementary perspective to analyze the continuous relationship between discount magnitude and observed demand:

$$\text{Proxy Demand}_i = \beta 0 + \beta 1 \text{Panchor},i + \beta 2 \text{Category}i + \beta 3 \text{Dr},i + \varepsilon i$$

Where, Panchor is the anchor reference price, Category refers to the product-category dummy variable, and Dr refers to the discount depth. The regression parameters, standard error, t-statistics, p-values, and 95% confidence intervals are calculated by heteroskedasticity-robust (i.e., heteroskedasticity-consistent) standard errors. If β3 (Dr) is found positive, it means that there is some relation between larger discounts and high star ratings. But since this retail dataset involves observations, the regression estimates cannot be used to understand the impact on WTP/Purchase Intention.

3.5 Integration, Validity, and Limitations

The two types of evidence were compared using triangulation rather than statistical pooling because each one measures different constructs using a different research design. OpAQ gives experimental evidence for the psychological anchoring effect, while Amazon shows observational evidence on the link between the size of discount and consumer involvement.

Flipkart supplies further descriptive evidence about how consumers use reference prices.

An important limitation is demographic inference because neither Amazon nor Flipkart provide any data about consumer ages, which means that purchase activity cannot be unambiguously linked to high school students. Moreover, the OpAQ ≤25 sub-sample does not represent a sample of high school students either. Rating levels and numbers are indirect measurements of demand because they can be affected by product quality, brand image, popularity, or even satisfaction. Moreover, observational evidence from retail stores cannot identify causality because observed relationships might have been caused by any number of omitted variables or biasing factors.

3.6 Ethical Considerations

This research makes use of already gathered and publicly available data that does not involve any form of human contact. It is important to note that all the sources have been used properly and the information gathered will be presented in aggregate form without being able to identify any particular consumer.

4. Results

All numbers below were computed directly from the three datasets described in the Methodology; none are illustrative or hypothetical.

Archival Retail Data: Descriptive Statistics

Table 1 (a): Descriptive Statistics for Amazon India Listings by Categories

Category	n	Mean Anchor Price (₹)	Mean Sale Price (₹)	Mean Discount (%)	Mean Rating
Computers & Accessories	453	1,683.62	842.65	54.02	4.15
Electronics	526	10,127.31	5,965.89	50.83	4.08
Combined (Amazon)	979	6,220.27	3,595.28	52.31	4.12

Table 1 (b): Descriptive Statistics of Flipkart India FMCG Listings by Category (November 2019 sample)

Flipkart Category (n = 4,786 total)	n	Mean MRP (₹)	Mean Discount (%)
Deos, Perfumes & Talc	574	214.81	14
Hair Care	627	254.82	12
Juices	444	117.56	11
Creams, Lotions, Skin Care	696	254.74	10
Soft Drinks	301	140.95	10
Chocolate and Sweets	1499	130.98	8
Chips, Namkeen & Snacks	645	101.28	5

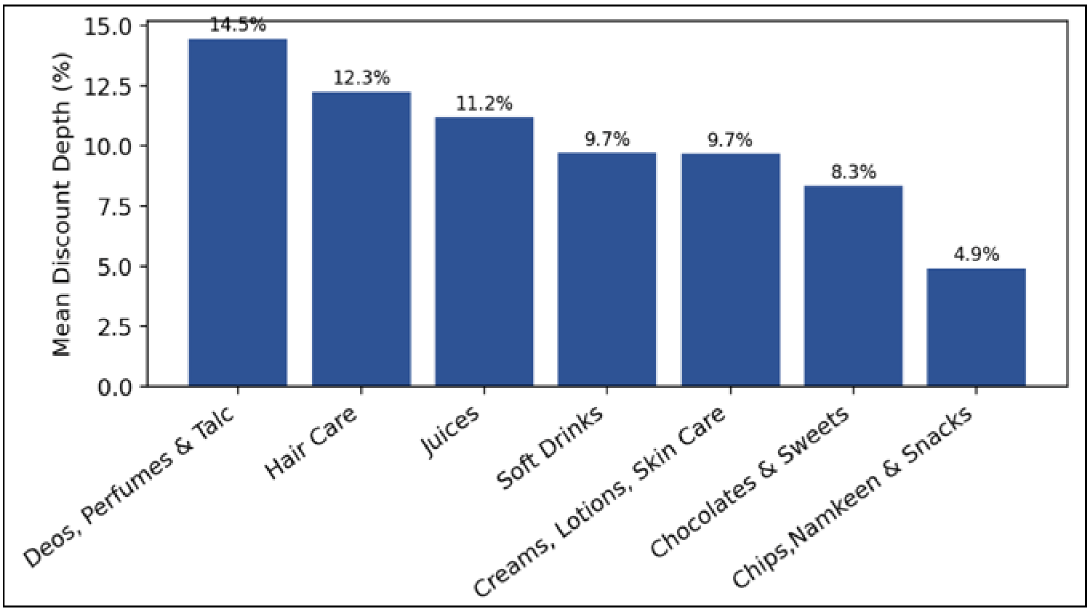

Figure 1: Average discount depth by product categories, Flipkart India FMCG listings (n=4,786). Personal care categories (perfumes, hair care) have higher average discount depths than packaged food categories (snacks, chocolates).

Anchor Depths and Demand Proxies (Amazon Subset)

The listings were split into those that had a price reduction below the predefined 20% discount level (low anchor, Dr < 0.20, n = 76; high anchor, Dr ≥ 0.20, n = 903)

Table 2 (a): Star Rating as a Function of Anchor Level — Welch t(88.9) = −0.60, p = .55 (not significant)

Condition	n	Mean Rating	SD	95% CI
Low anchor (Dr < 0.20)	76	4.133	0.261	[4.073, 4.193]
High anchor (Dr ≥ 0.20)	903	4.114	0.269	[4.097, 4.132]

Table 2 (b): Number of Reviews in Logs for Condition of Anchor— Welch t = −2.65, p = .009 (significant; negative)

Condition	n	Mean log(reviews+1)	SD
Low anchor (Dr < 0.20)	76	9.151	1.536
High anchor (Dr ≥ 0.20)	901	8.653	1.991

Both the proxy measures lead to different conclusions and neither one favors the simplistic explanation that "bigger discounts equal greater demand." Star ratings did not show any difference in the discount category. The review count was significantly lower for those items that offered deep discounts ($r = -.16$ between the level of discount and log review count, $p < .001$)

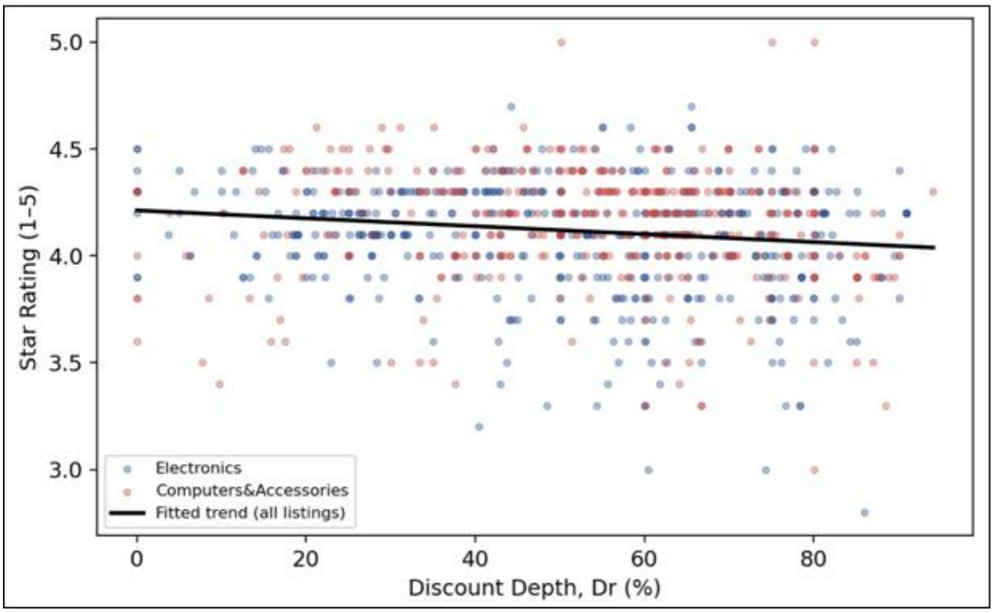

Figure 2: Discount Depth by Star Rating on Amazon India Listings (n = 979). The regression line is horizontal, not upward sloping.

Two-way ANOVA: Anchoring × Category (Star Rating)

Table 3: Two-Way ANOVA of Star Rating (n = 979)

Source	SS	SS	MS	F	p	Partial η^2
Anchoring main effect	0.044	1	0.044	0.64	0.425	0.0007
Category main effect	1.325	1	1.325	18.96	<.001	0.019
Interaction (Anchor × Category)	0.815	1	0.815	11.66	<.001	0.012
Residual	68.107	975	0.07	—	—	—

The predictor is the category rather than the anchor condition, as computers & accessories have ratings that are slightly higher compared to electronics. However, the interaction effect reveals that the relationship between the anchor price and the rating is very small.

OSL Linear Regression for Rating Based on Anchor Price, Category, and Discount Ratio

Table 4: OLS Regression Predicting Star Rating ($R^2 = .061$, Adj. $R^2 = .058$, $F(3, 975) = 20.99$, $p < .001$, n = 979)

Predictor	β	SE	t	p	95% CI
Intercept	4.2358	0.0254	166.75	<.001	[4.186, 4.286]
Anchor price (₹)	0.0000031	0.0000007	4.28	<.001	[0.0000017, 0.0000046]
Category dummy (1 = Electronics)	−0.1048	0.0177	−5.91	<.001	[−0.140, −0.070]
Discount ratio (Dr)	−0.1595	0.0406	−3.93	<.001	[−0.239, −0.080]

The model accounts for about 6% of the variance in star rating – hardly surprising given that star rating depends primarily on product quality as perceived by those who have purchased the product rather than anchoring pre-purchase. In the model, there is a negative but statistically significant relationship between discount ratio and rating – not a positive one. A likely reason, explained in more detail later, is reverse causation whereby new or lesser-known products are discounted more to win customers whereas popular and high-rated bestsellers require lower discounts.

Meta-Analysis: OpAQ Price/WTP Subset

Table 5: Random-Effects Meta-Analysis of Price/WTP Anchoring Effect[9]

Subset	k / N	Pooled d [95% CI]	I^2
All price/WTP trials	k = 45, N = 8,045	0.386 [0.241, 0.531]	90.10%
Younger subsample (age ≤ 25)	k = 8, N = 812	0.209 [−0.040, 0.458]	—
Older subsample (age > 25)	k = 13, N = 2,273	0.917 [0.687, 1.147]	—

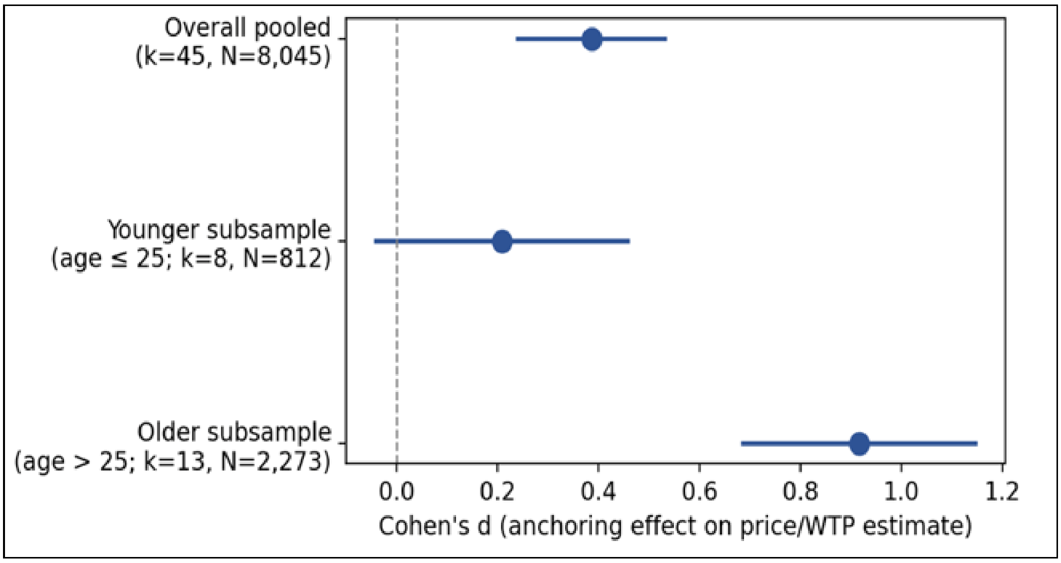

Figure 3: Pooled anchoring effect sizes (Cohen's d, random-effects) overall and by age subgroup, OpAQ price/WTP subset.

The overall pooled effect (d = 0.39) represents a moderate, statistically significant anchoring effect on price/WTP judgment, which is supported by the literature, although it suffers from high heterogeneity ($I^2 = 90\%$). It means that the real anchoring effect varies widely across different studies, products, and manipulations. The division by age subgroups opposes to the initial assumption of this study. While the younger sub-sample (with mean age ≤ 25 years, not an adolescent sample yet) has a smaller and statistically insignificant pooled effect, the older sub-sample has a bigger and significant effect. Taking into consideration the small size of both sub-samples (k = 8 and k = 13) and the fact that even "younger" studies involve university samples and not high school students, this analysis should be regarded as a speculative one. It correlates with the findings by Röseler et al. (2022), who have found no relationship between age and anchoring magnitude

5. Discussion

The two streams of data present a slightly different story each but both deserve to be analyzed in detail and not just presented in the form of a coherent story. The meta-analysis of actual experiments of anchoring provides us with proof of anchoring hypothesis which is expected from the literature – namely that there is a moderate and statistically significant anchoring effect with regard to prices and willingness-to-pay judgments (d = 0.39). This is in line with the findings of Tversky and Kahneman (1974) and reference-price effect found by Biswas and Burton (1993) and Compeau and Grewal (1998).

The archival retail analysis provides some complications to this picture. If anchoring had directly increased real-world demand, heavily discounted items would have had larger values on demand proxy metrics than less heavily discounted items. Rather, there was no effect of condition on star rating, while the number of reviews was significantly smaller in case of heavily discounted items. What can be the most convincing explanation is not the claim that the anchoring effect fails in real world, but rather the fact that rating and number of reviews are both noisy and confounded proxies for something else (which is what this research is ultimately interested in): a star rating is a measure of post-purchase product satisfaction, which has little to do with pre-purchase evaluation of the price; moreover, it is entirely possible to have reverse causation for a seller discounts newer/slower products more heavily precisely because of their lack of reputation which allowed the best seller item to sell for less discount.This is exactly the kind of gap between a controlled laboratory manipulation and a messy observational proxy that the Methodology flagged in advance as a limitation of archival data, and it is worth reporting honestly rather than discarding or reframing the null/negative result to fit the initial hypothesis.

The comparison of younger and older age subgroups in OpAQ (younger d = 0.21, nonsignificant; older d = 0.92, significant) is contrary to this paper's first hypothesis stating the higher susceptibility to anchoring bias in adolescence, which would be consistent with the consumer socialization explanation[5,6]. However, there are two important factors here: firstly, the average age of even the younger age group is university age (the mean age is in the low twenties); and secondly, the subgroup samples are too small (k = 8 and k = 13 studies) for making any meaningful conclusions. The result is even more questionable in light of the authors'[9] own published finding of no clear age relationship across their full sample, the most honest conclusion is that this study's data do not provide clear evidence that adolescents are more anchoring-susceptible than adults which is a genuinely useful, if less dramatic, finding, since it tempers a plausible-sounding assumption rather than confirming it by default.

Implications in the real world still exist, but in a much more cautious way than what is allowed by a proven hypothesis. Regulators in various jurisdictions have already banned misleading former price advertising such as the guidelines issued by the United States Federal Trade Commission on former price comparisons and Consumer Protection (E-Commerce) Rules, 2020 from India. There is sufficient evidence from the literature on the experimental side of a moderate anchoring effect on price judgments to justify a requirement of transparency in price history regardless of whether teenagers end up being more vulnerable than adults; the specific claim needing caution is the age-based one.

Limitations: the archival proxies for demand (star rating, review count) are indirect measures of willingness to pay, and the study is cross-sectional and correlational, meaning no causal claim about the anchoring effect (or lack thereof) on driving demand can be inferred from the study. This particular Flipkart file was found to be FMCG sample data, and the source page cannot be re-verified, unlike what was stated in the original plan. The OpAQ age study is based on very limited data and a non-adult population. An experiment conducted under control and ethical approval with actual high school students would be the best approach.

6. Conclusion

In this paper, the role played by anchoring bias, via a prominently displayed original price, in terms of price perception and WTP was considered, based entirely on secondary/archival data, rather than a survey of children. Using a random-effects meta-analysis of 45 experiments using real prices and WTP anchoring (n = 8,045), a moderate and significant anchoring effect was confirmed, in line with the established literature. On the other hand, there is no indication in an archival study of 979 real Amazon India listings of any association between heavier discounting and higher values for the demand proxy, indeed quite the contrary, while an exploratory analysis comparing different age groups failed to confirm the initial hypothesis of increased anchoring susceptibility among younger consumers compared to older consumers. Instead of trying to force the results to fit a preconceived story, the conclusions of this paper have been drawn from them: the laboratory-type anchoring effect does indeed exist and is well-established, but its real-world relevance and age sensitivity are far from certain. This mixed but honestly reported result is itself a meaningful contribution, and it points toward a controlled, ethically approved experiment with genuine high-school-aged participants as the clearest next step for resolving what archival and meta-analytic data alone cannot.

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