

Algorithmic Desire Dysmorphia: How Short-Form Video Recommendation Systems Create Phantom Preferences and Erode Consumers' Ability to Distinguish Authentic Desire from Algorithmically Induced Craving

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Abstract:

➤ Background:

Short-form video platforms increasingly personalize users' feeds through recommendation systems that repeatedly expose them to products, aesthetics, and consumption narratives. This study examines whether repeated algorithmic exposure is associated with changes in perceived product interest and uncertainty about the origins of consumer desire.

➤ Methods:

The manuscript analyzes aggregate descriptive survey information supplied for 200 participants in India who reported short-form video use. Measures cover platform use, algorithmic awareness, perceived personalization, repeated exposure, hypothetical pre- and post-exposure interest, and consumer behaviors such as saving, searching, purchasing, and later questioning a purchase. Results are reported descriptively because the supplied information is aggregate rather than respondent-level raw data.

➤ Results:

Instagram Reels and YouTube Shorts were the most commonly reported platforms. Approximately 70% of participants reported often or very often seeing the same product repeatedly, 62.5% reported becoming interested after repeated exposure, and 47.5% reported searching for a product after such exposure. About 37.5% reported purchasing primarily because of repeated exposure, 65% reported saving/searching/wishlisting products, and 42.5% reported later wondering why they wanted a purchased item. In the hypothetical scenario, mean interest increased from approximately 2.2 before exposure to 5.1 after exposure on a 1–7 scale.

➤ Conclusions:

The descriptive pattern is consistent with the possibility that repeated personalized exposure can amplify perceived relevance and consumer desire, while users may simultaneously recognize that recommendation systems shape what they see. The findings should not be interpreted as causal or nationally representative without respondent-level data and inferential testing.

Keywords: *Algorithmic Recommendation; Short-Form Video; Consumer Behavior; Personalization; Preference Formation; Consumer Desire; Social Media; Instagram Reels; Youtube Shorts.*

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I. INTRODUCTION

Short-form video platforms have changed the way consumers encounter products, lifestyles, aesthetics and

trends. Recommendation systems continuously select content based on users' previous interactions, creating feeds that can appear increasingly tailored to individual interests. This personalization raises an important question for consumer

research: when a person develops an interest in a product after seeing it repeatedly, to what extent does that interest reflect an existing preference and to what extent might it have been reinforced through algorithmic exposure?

The central issue examined in this paper is not simply whether algorithms influence purchasing behavior. It is whether repeated recommendation can change the consumer's perception of the origin of desire. A product that initially appears irrelevant may become familiar through repeated exposure. Familiarity may make it seem relevant, and relevance may eventually be interpreted as personal taste. The resulting preference can feel authentic even when the consumer recognizes that an algorithm played a role in repeatedly presenting the product.

➤ Research Objectives

- To examine users' awareness of short-form video recommendation algorithms.
- To measure perceived personalization of recommended content.
- To examine the frequency of repeated exposure to products, trends and lifestyles.
- To assess whether repeated exposure is associated with increased consumer interest and search behavior.
- To examine whether users perceive algorithmically reinforced preferences as personal preferences.
- To explore whether repeated exposure is associated with purchase intention.

➤ Research Questions

- RQ1. To what extent do short-form video users perceive recommendations as personalized to their interests?
- RQ2. How frequently does repeated exposure to products and lifestyles occur?
- RQ3. Is repeated exposure associated with increased interest and consumer search behavior?
- RQ4. Do consumers experience uncertainty about whether a preference existed before repeated algorithmic exposure?
- RQ5. How does the reported pattern differ across age groups?

II. CONCEPTUAL FRAMEWORK

The proposed framework begins with algorithmic personalization. Personalized recommendation increases the

probability that a user will encounter similar products or themes repeatedly. Repeated exposure can increase familiarity and attention. Familiarity may then increase perceived relevance, which can contribute to preference internalization and consumer desire. Desire may subsequently lead to searching, saving, wishlisting and purchasing.

Proposed pathway: Algorithmic personalization → repeated exposure → familiarity/attention → perceived relevance → preference internalization → perceived desire → purchase intention.

Algorithmic awareness is treated as a potential moderating factor because users may recognize that their feed is personalized while still experiencing recommended products as genuinely desirable.

➤ Hypotheses

- H1. Greater repeated exposure is associated with higher perceived interest in a product.
- H2. Greater repeated exposure is associated with greater preference change.
- H3. Higher perceived personalization is associated with stronger preference internalization.
- H4. Stronger preference internalization is associated with higher purchase intention.
- H5. Algorithmic awareness may moderate the relationship between repeated exposure and preference internalization.
- H6. Products with lower initial interest may show larger preference changes following repeated exposure.

III. METHODOLOGY

➤ Research Design

The study uses a quantitative, cross-sectional survey design supplemented by a hypothetical repeated-exposure scenario. The questionnaire measured demographics, platform usage, algorithmic awareness, perceived personalization, repeated exposure, preference-related behavior and purchase intention.

➤ Sample

The supplied dataset contains 200 respondents in India. The reported age distribution was 45 respondents aged 18–20, 50 aged 21–23, 40 aged 24–26, 30 aged 27–30, 20 aged 31–35 and 15 aged 36 or above. All 200 reported respondents selected the consent option.

Table 1 Sample

Age group	Respondents	Percentage
18–20	45	22.5%
21–23	50	25.0%
24–26	40	20.0%
27–30	30	15.0%
31–35	20	10.0%
36+	15	7.5%

➤ Measures

Algorithmic awareness was measured through Q9–Q13 using a 5-point agreement scale. Perceived personalization was measured through Q14–Q17. Repeated exposure was assessed through Q18–Q20. Q21–Q25 measured responses to the hypothetical scenario on 7-point scales. Q26–Q30 assessed preference internalization and uncertainty, Q31 measured perceived contribution of exposure, Q32–Q34 assessed real-world consumer behavior, and Q35 provided an optional open-ended response.

➤ Scenario

Participants were asked to imagine having little or no initial interest in a product category, followed by repeated exposure to videos about that category from different

creators. They then rated initial interest, post-exposure interest, desire, search likelihood, purchase likelihood and the perceived contribution of repeated exposure.

➤ Analysis

The current version uses the aggregate descriptive figures supplied by the researcher. Inferential tests cannot be calculated without the individual response file.

IV. RESULTS

➤ Platform Usage

Instagram Reels and YouTube Shorts were the dominant platforms in the supplied data. Multiple platform selections were possible, so percentages do not sum to 100%.

Table 2 Platform Usage

Platform	Approx. respondents	Approx. share
Instagram Reels	185	92.5%
YouTube Shorts	170	85.0%
Facebook Reels	90	45.0%
TikTok	25	12.5%

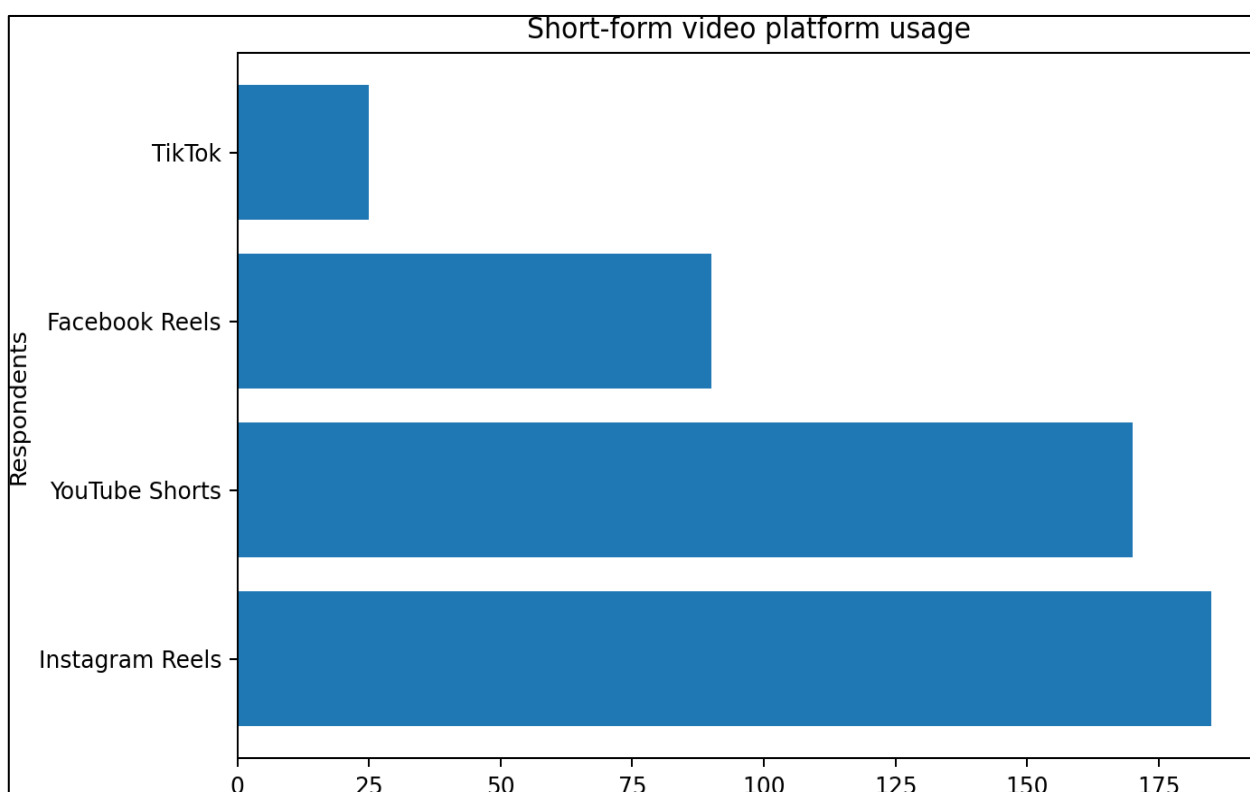


Fig 1 Short-Form Video Platform Usage in the Supplied Sample.

➤ Repeated Exposure

Approximately 140 respondents (70%) reported often or very often seeing the same product, brand, trend or lifestyle repeatedly. Approximately 125 (62.5%) reported often or very often becoming interested after repeated exposure, while approximately 95 (47.5%) reported often or very often searching after repeated exposure.

Table 3 Repeated Exposure

Measure	Approx. respondents	Percentage
See same product repeatedly	140	70.0%
Become interested after repetition	125	62.5%
Search after repetition	95	47.5%

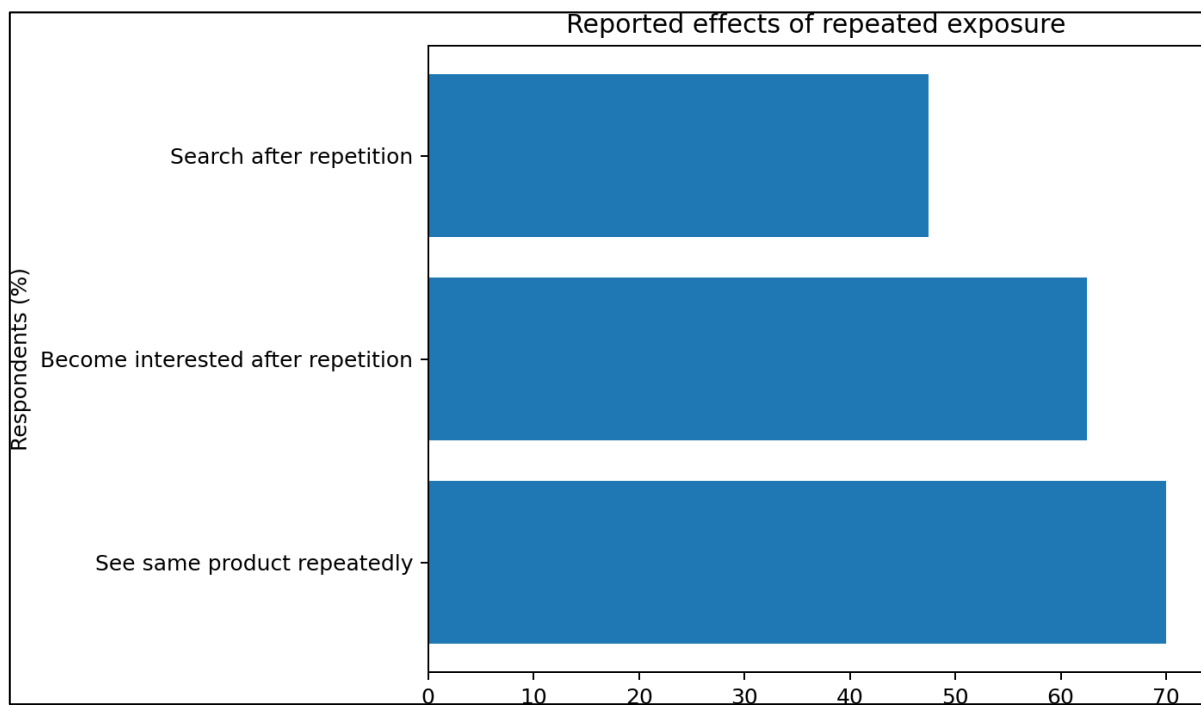


Fig 2 Reported Effects of Repeated Exposure.

➤ *Purchase and Preference-related Behavior*

Approximately 130 respondents (65%) reported saving, searching for or wishlisting a product after repeated exposure. Approximately 75 (37.5%) reported purchasing something primarily because they repeatedly encountered it, and approximately 85 (42.5%) reported later wondering why they wanted a purchase.

Table 4 Purchase and Preference-Related Behavior

Behavior	Approx. respondents	Percentage
Saved/searched/wishlisted	130	65.0%
Purchased primarily after exposure	75	37.5%
Later questioned the desire	85	42.5%

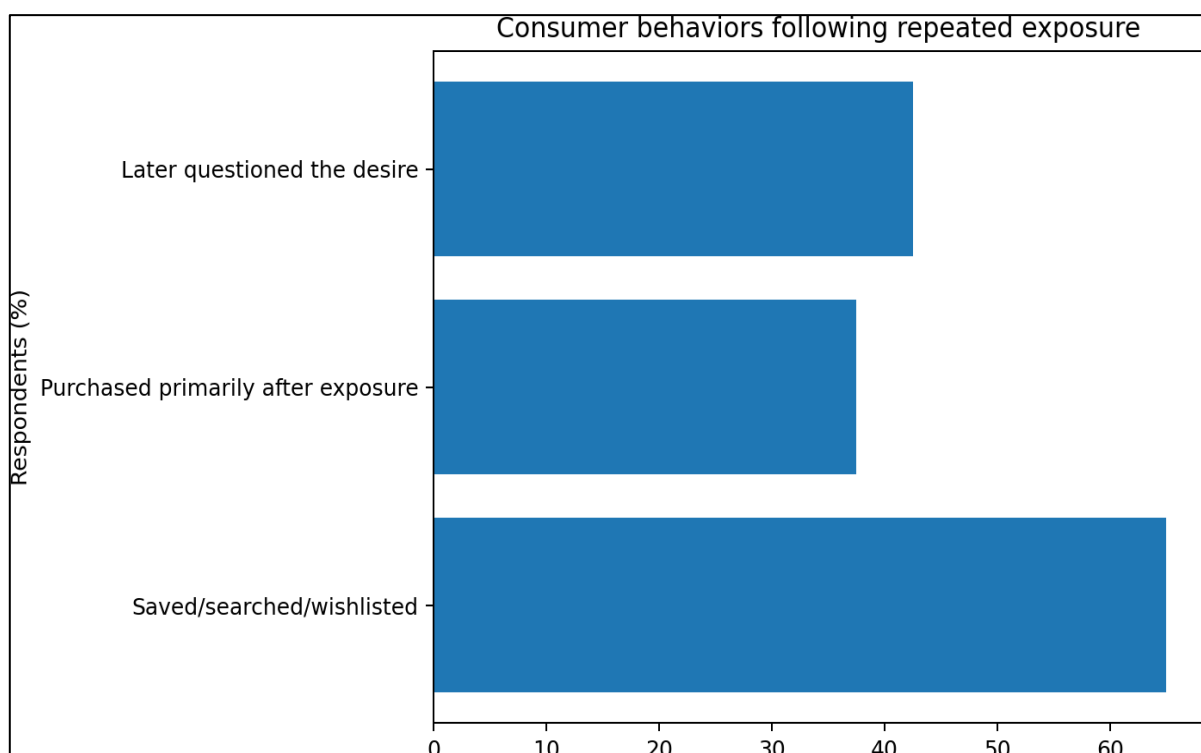


Fig 3 Consumer Behaviors Following Repeated Exposure.

➤ *Hypothetical Scenario*

The strongest descriptive pattern is the reported difference between initial and post-exposure interest. Average initial interest was approximately 2.2/7, compared with approximately 5.1/7 after repeated exposure, a descriptive increase of 2.9 points.

Table 5 Hypothetical Scenario

Scenario measure	Mean (1–7)
Initial interest	2.2
Post-exposure interest	5.1
Want product	5.0
Search likelihood	5.3
Purchase likelihood	4.1
Exposure contribution	5.2

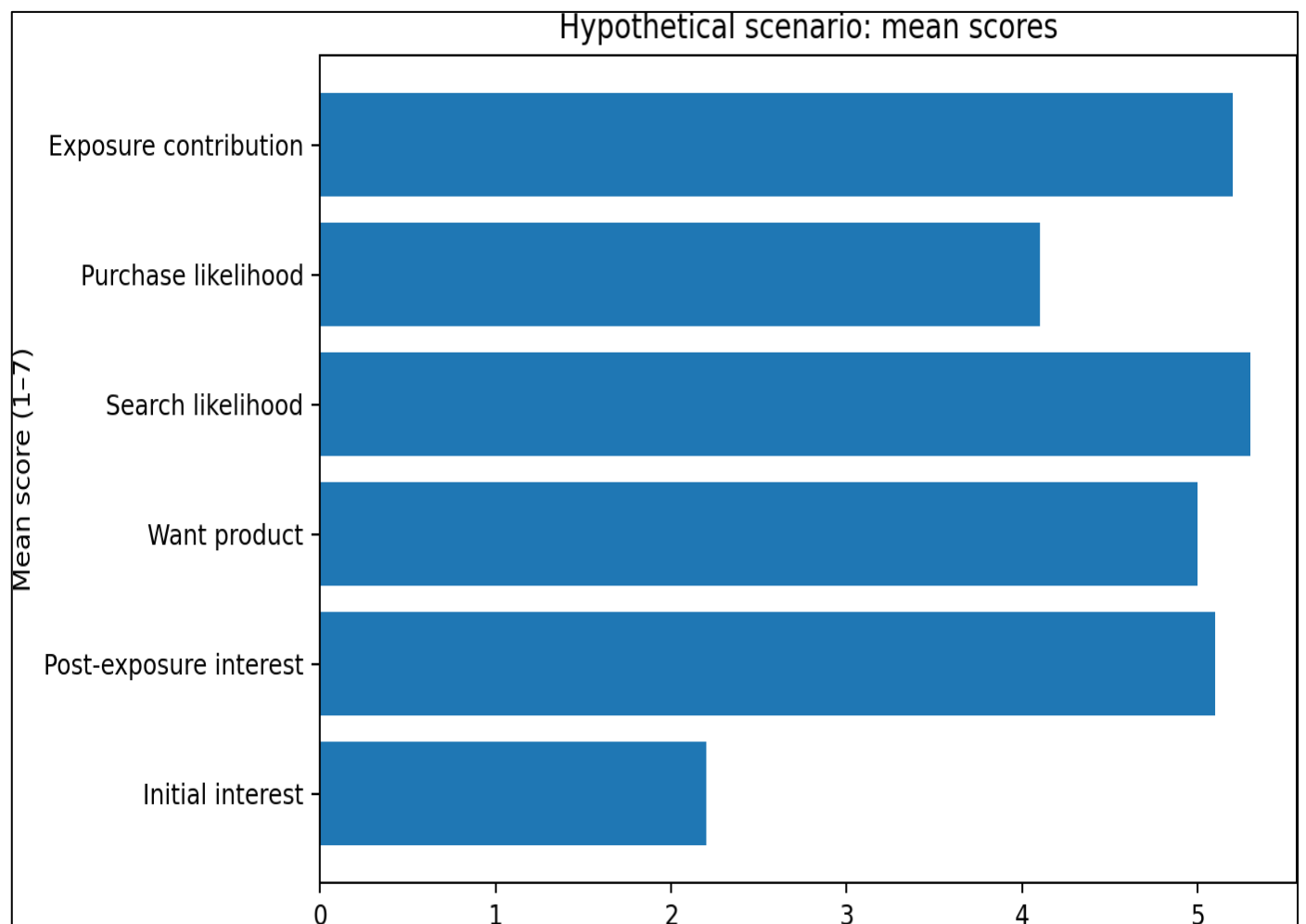


Fig 4 Mean Scores Reported for the Hypothetical Repeated-Exposure Scenario.

➤ *Age-group Pattern*

The supplied age-group summaries indicate a larger descriptive preference increase among younger groups. For respondents aged 18–20, 21–23, 24–26 and 27–30, the approximate initial-to-post-exposure changes were +3.5, +3.8, +3.1 and +2.5 points respectively.

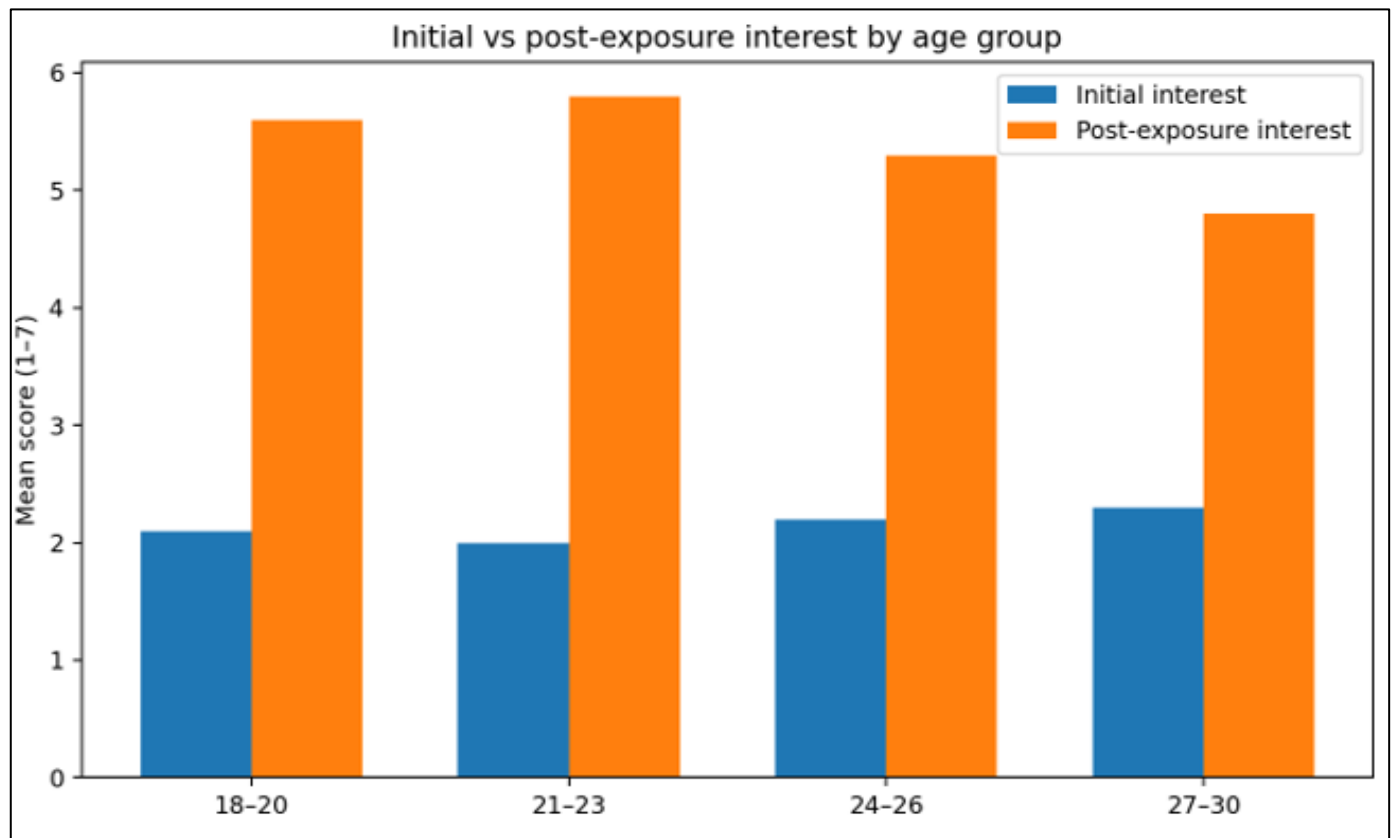


Fig 5 Approximate Initial and Post-Exposure Interest for Respondents Aged 18–30.

V. DISCUSSION

The supplied descriptive findings are consistent with the paper's central proposition that repeated algorithmic exposure can make previously unfamiliar products feel increasingly familiar and relevant. The hypothetical scenario is particularly notable because reported average interest increased from approximately 2.2 to 5.1 on a 7-point scale. This does not establish causation, but it provides a clear descriptive basis for investigating preference formation under repeated personalized exposure.

The behavioral measures show a graded pattern. More respondents reported saving, searching or wishlisting products than reported purchasing primarily because of repeated exposure. This suggests that algorithmic influence, if present, may occur across several stages of consumer consideration rather than only at the point of purchase.

The reported 42.5% who had bought something and later wondered why they wanted it is relevant to the concept of preference-source uncertainty. However, this measure cannot determine whether an algorithm caused the desire. Post-purchase doubt can arise for many reasons, including impulse buying, changing circumstances, price concerns or ordinary consumer reflection.

The age-group pattern is also descriptive rather than inferential. Younger respondents in the supplied summaries showed larger changes in scenario interest, while older respondents were described as more likely to emphasize need, price and independent reviews. Respondent-level analysis

would be required before concluding that age moderates algorithmic preference formation.

VI. THEORETICAL IMPLICATIONS

- Recommendation systems may be considered environments in which preferences are not only revealed but potentially reinforced.
- Repeated exposure may operate through familiarity and perceived relevance before a consumer reaches a purchase decision.
- The distinction between pre-existing preference and perceived preference formation can help consumer research examine subjective autonomy in personalized media environments.
- Algorithmic awareness should be measured rather than assumed to eliminate influence.

VII. LIMITATIONS

- The available data are aggregate and approximate rather than respondent-level.
- The sample should not be described as representative of all Indian consumers.
- The study relies on self-reported behavior and perceptions.
- The hypothetical scenario measures stated responses rather than observed purchasing behavior.
- Descriptive figures cannot establish causality or statistical significance.

- Some age-group summaries are incomplete, preventing full age-based statistical comparison.

VIII. RECOMMENDED STATISTICAL ANALYSIS FOR THE RAW DATASET

- Calculate descriptive statistics including mean, standard deviation and frequency distributions.
- Test internal consistency of the multi-item scales using Cronbach's alpha.
- Test correlations between repeated exposure, personalization, preference internalization and purchase intention.
- Use a paired-samples test for individual-level initial versus post-exposure interest.
- Use regression to test whether repeated exposure predicts preference internalization and purchase intention.
- Test whether algorithmic awareness moderates the relationship between repeated exposure and preference internalization.
- Use appropriate age-group comparison tests and report effect sizes and confidence intervals.

IX. CONCLUSION

This study examines a contemporary consumer-behavior problem created by highly personalized short-form video environments: the possibility that repeated recommendations may influence not only what consumers encounter, but how they understand their own preferences. The supplied aggregate results show frequent repeated exposure, substantial interest and search behavior following repeated exposure, and a pronounced descriptive increase in hypothetical product interest from 2.2 to 5.1 on a 7-point scale.

The findings do not demonstrate that recommendation algorithms cause consumers to want products they would otherwise reject. Instead, they provide preliminary descriptive evidence supporting further investigation into how familiarity, personalization and repeated exposure may become incorporated into consumers' subjective sense of taste.

Future research should use respondent-level data, experimental or longitudinal designs, and statistical testing to determine whether the observed relationships remain after accounting for pre-existing interests and other consumer characteristics.

➤ Funding Statement

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors. No funder had a role in the study design, data analysis, interpretation, manuscript preparation, or decision to submit the manuscript.

➤ Ethics Statement

The manuscript reports analysis of aggregate survey information. No identifiable personal data, biological samples, or clinical records were used in the analyses presented here. The supplied materials do not document institutional ethics committee approval or a formal ethics reference number; accordingly, no claim of ethics approval is made in this manuscript. If the underlying survey was independently administered to human participants, the authors should insert the applicable institutional ethics/IRB approval or exemption information before submission.

➤ Data Availability

The study is based on aggregate survey information supplied for 200 participants in India. The underlying respondent-level dataset was not available to the author for the analyses presented in this manuscript; therefore, raw-data files are not publicly deposited with this article. The aggregate figures used for the tables and descriptive analyses are reported in the manuscript.

➤ Conflict of Interest

The author declares that there are no known financial, personal, or professional conflicts of interest that could have influenced the work reported in this manuscript.

AUTHOR CONTRIBUTIONS

Shraddha Sharma: conceptualization, methodology, survey instrument development, data curation, analysis and interpretation of the supplied aggregate data, writing—original draft, writing—review and editing, visualization, and project administration. The author approved the final manuscript.

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➤ *Data Note:*

This paper uses the aggregate figures supplied by the researcher for 200 respondents. The figures are approximate and do not include respondent-level observations. Therefore, this draft reports descriptive results only; it does not invent statistical significance, standard deviations, reliability coefficients, regression results, or p-values. The raw Google Forms export should replace these aggregate figures before submission as a final empirical paper.

APPENDIX A: SURVEY CONSTRUCTS

Construct	Items
Algorithmic awareness	Q9–Q13
Perceived personalization	Q14–Q17
Repeated exposure	Q18–Q20
Hypothetical preference change	Q21–Q25
Preference internalization/source uncertainty	Q26–Q30
Exposure contribution	Q31
Behavioral indicators	Q32–Q34
Open-ended experience	Q35