

Behavioural Segmentation and the Privacy Personalisation Paradox in Indian Digital Advertising

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ABSTRACT

This paper examines behavioural segmentation in digital advertising in India, the role of which is to identify how consumer response is affected by privacy issues and customisation. The survey data on 221 internet users in India were also analysed in terms of reliability testing, factor analysis, K-means clustering, regression and correlation using quantitative techniques. Two major behavioural variables were found to be Impulsive Ad Engagement and Trust and Information Sensitivity, which accounted for 65.9 per cent of the variance. The emergence of six profiles of consumers indicated various engagement behaviours and privacy orientation. Even though correlation analysis showed that there is a moderately positive relationship between privacy issues and the acceptance of personalised advertisements ($r = 0.540$, $p < 0.001$), the regression analysis showed that personalisation is a significant predictor of the behavioural response ($\beta = 0.7730$, $p < 0.001$). Its evidence indicates that when individualised advertising is carried out transparently and ethically, Indian consumers like it. Marketers must create campaigns that are both data-driven and personalised and privacy-focused so as to achieve a balance between relevance and responsibility in order to gain trust and interaction. Within the research paper, the data will contribute to the digital marketing literature by providing a behavioural segmentation model of ethical and personalised marketing of advertising in a growing market like India.

Keywords: Digital advertising, consumer behaviour, privacy, personalisation, behavioural segmentation, marketing ethics

1. Introduction

1.1 Background and Context

Digital advertising in India has expanded rapidly due to increasing internet penetration, smartphone adoption, and data-driven marketing technologies. The ability to personalise has taken a primary role, and now the advertisements can be tailored to the consumers and enhance engagement. Concurrently, increasing awareness about data tracking, profiling and misuse has heightened the issue of privacy. That is how the personalisation-privacy paradox is formed since users do not stop to think about the manner in which their data is handled and collected, as they appreciate the relevance of the ads. The digital population of India is very heterogeneous with regard to literacy, awareness, exposure to technology, and trust in online platforms. With the spread of AI-based targeting and the resulting heightened regulatory interest in the privacy rights of consumers, data protection tradeoffs and the value of personalisation to the privacy of consumers are critical to advertisers and policymakers based in India.

1.2 Research Problem

Although the digital landscape in India is rapidly developing, the empirical data on the effectiveness of personalised advertising in situations when privacy concerns co-exist are lacking. Prior research focuses primarily on Western markets, leaving a gap in understanding behavioural segmentation and privacy-personalisation dynamics in emerging economies like India.

1.3 Objectives of the Study

The study aims to:

1. Identify behavioural segments within Indian consumers exposed to digital advertising.
2. Examine the impact of personalisation on consumer behavioural responses.
3. Analyse how privacy concerns influence acceptance of personalised advertising.

2. Literature Review

2.1 Behavioural Segmentation and Digital Consumer Typologies

Wedel and Kamakura (2012) argue that market segmentation remains one of the most important marketing strategies that enable firms to divide their customers into more homogeneous groups to target and position them more specifically. The advancement of segmentation is no longer based on demographics, but also on behavioural and attitudinal aspects because of the spread of online interaction information. Segmenting customers based on their online behaviour, ad reaction, or purchasing frequency is called behavioural segmentation, and it provides a better insight into their tastes and desires (Dolnicar, 2019). K-means clustering and principal component analysis (PCA) are some of the analytical tools that are necessary today when trying to identify consumer patterns hidden in high-dimensional data (Wang, 2020).

2.2 Effectiveness of Personalisation and Behavioural Targeting

Digital advertising has replaced mass messaging with personalised communication, where relevance to individual customers will promote interaction, click-throughs and intent to convert (Bleier & Eisenbeiss, 2018). Personalised online advertisements have been demonstrated to impact positively, albeit the magnitude of such effects is lessened in relation to perceived intrusiveness, relevance, and trust. Experimental studies show that personalisation contributes to brand favourability and purchase intention, yet can also lead to resistance when the advertisement feels intrusive (Aguirre et al., 2015). Despite ethical and transparency concerns, emerging technologies such as artificial intelligence (AI) continue to influence the practice of personalisation.

2.3 Privacy Concerns and Ethical Implications in Digital Advertising

The personalisation–privacy paradox is one of the key contradictions in digital marketing: customers appreciate relevancy but remain suspicious of data tracking and profiling (Boerman et al., 2017). Privacy calculus theory states that consumers weigh perceived benefits against risks when deciding whether to accept data use (Cai et al., 2023). Empirical studies show that actual disclosure often does not match stated concerns, known as the privacy paradox (Kokolakis, 2017). Transparency and brand trust have been shown to reduce privacy concerns and improve acceptance of customised advertisements.

3. Research Methodology

3.1 Research Design

The study adopted a quantitative, cross-sectional survey design to examine how personalisation and privacy concerns influence behavioural responses to digital advertising in India. This design is appropriate for identifying statistical relationships between constructs and for conducting segmentation using multivariate techniques.

3.2 Sample and Data Collection

Primary data were collected from 221 adult internet users in India through an online questionnaire distributed via digital channels. A snowball sampling approach was used, reflecting typical practices in exploratory digital advertising research. The sample size of 221 is adequate for factor analysis, clustering and regression.

3.3 Measurement of Constructs

All constructs were measured using validated five-point Likert scales. Behavioural Response captured involvement, attention to ads and purchase intention; Personalisation assessed perceived relevance, usefulness and comfort with tailored ads; and Privacy Concern measured perceived risks, information visibility and discomfort with data use.

3.4 Data Analysis

Data were coded and analysed using Python libraries. Reliability was evaluated using Cronbach's Alpha, and Exploratory Factor Analysis (PCA with Varimax rotation) was conducted after confirming sampling adequacy through KMO and Bartlett's tests. K-Means clustering identified behavioural segments based on silhouette scores. Regression (OLS) examined the effect of Personalisation on Behavioural Response, and Pearson's r and Spearman's ρ assessed associations between Privacy Concern and Personalisation Acceptance.

4. Hypotheses of the Study

Based on the theoretical background and literature review, the following hypotheses were formulated:

H1: Digital advertising audiences in India can be segmented into distinct behavioural groups that differ in engagement, responsiveness and privacy orientation.

H2: Higher perceived personalisation of digital advertising leads to a stronger behavioural response.

H3: Consumer acceptance of personalised advertising decreases when privacy concerns are greater.

5. Data Analysis & Interpretation

5.1 Reliability Analysis

Cronbach's Alpha values showed strong internal consistency across constructs: Behavioural Response ($\alpha = 0.739$), Personalisation ($\alpha = 0.706$), and Privacy Concern ($\alpha = 0.830$). All constructs surpassed the minimum reliability threshold, confirming stable respondent interpretation.

Table 1: Reliability statistics for study constructs

Construct	Cronbach's α	Interpretation
Behavioural Response	0.739	Acceptable reliability
Personalisation	0.706	Acceptable reliability
Privacy Concern	0.830	High reliability

Source: Computed using Python

5.2 Descriptive Statistics and Item-Total Correlation Diagnostics.

All items exceeded the minimum item–total correlation threshold of 0.20, indicating meaningful contribution to each construct. Privacy Concern had the highest mean ($M = 3.83$), followed by Personalisation ($M = 3.50$) and Behavioural Response ($M = 3.42$). Variability levels indicate suitability for multivariate analyses.

Table 2. Descriptive Statistics of Key Constructs (n = 221)

Variable	Mean	Std. Deviation	Minimum	Maximum
Behavioural Response	3.42	0.59	1.83	5.00
Personalisation	3.50	0.52	1.71	5.00
Privacy Concern	3.83	0.63	1.60	5.00

Source: Computed using Python

5.3 Factor Analysis for Behavioural Variables

Sampling adequacy was confirmed ($KMO = 0.764$; Bartlett's Test $p = 0.001$). PCA with Varimax rotation extracted two components with eigenvalues > 1 , explaining 65.9% of variance. The components represented: Impulsive Ad Engagement (impulse, discount-driven, ad frequency) and Trust and Information Sensitivity (brand trust, information value, transparency)

Table 3. Rotated Component Matrix (Varimax)

Behavioural Item	Factor 1	Factor 2	Interpretation
I often make impulsive purchases after seeing online ads	0.684	–	Impulsive ad-driven behaviour
I pay more attention to ads with discounts or offers	0.768	–	Price-driven responsiveness
I consider a product when I see repeated ads	0.743	–	Ad frequency influence

I trust ads from well-known brands	–	0.483	Brand-trust orientation
I prefer ads with useful product information	–	0.648	Information-based engagement
I trust transparent brands in data practices	–	0.592	Ethical trust dimension

Source: Computed using Python

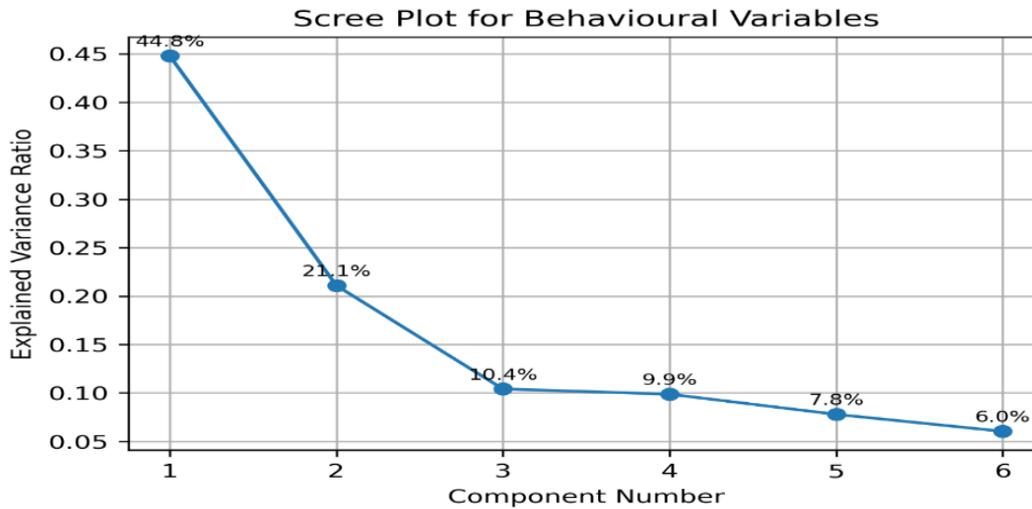


Figure 1. Scree Plot showing two-component solution for behavioural items.

The scree plot indicates a steep drop beyond the second component, which proves that a factor solution is what captures the bulk of the variance in behavioural responses.

5.4 Cluster Analysis (K-Means Segmentation)

K-Means created six different clusters (maximum silhouette = 0.185). The clusters represented different behavioural patterns, engaged ones, cautious, privacy-driven, indifferent, and passive, which showed that targeted strategies of personalisation should be applied to segments.

Table 4. Cluster Profile Based on Mean Composite Scores

Cluster	Behaviour Score	Personalisation Score	Privacy Score	Approx. % of Respondents	Interpretation
C1 (n = 39)	3.52	3.64	4.01	17.6%	Balanced Realists – Moderately engaged, appreciate personalised ads, and value privacy.
C2 (n = 38)	3.24	3.44	3.65	17.2%	Sceptical Observers – Moderate response to ads and personalisation, cautious about privacy.
C3 (n = 18)	2.76	3.17	4.51	8.1%	Privacy-Driven Consumers – Low ad engagement, strong preference for data protection.
C4 (n = 19)	3.25	3.40	3.78	8.6%	Indifferent Viewers – Neutral across all

					dimensions; low emotional involvement.
C5 (n = 62)	4.01	3.86	4.10	28.1%	Highly Engaged Seekers – Strongly responsive to ads and personalisation, yet privacy-aware.
C6 (n = 45)	2.99	3.11	3.20	20.4%	Passive Consumers – Low engagement and minimal concern about privacy.

Source: Computed using Python

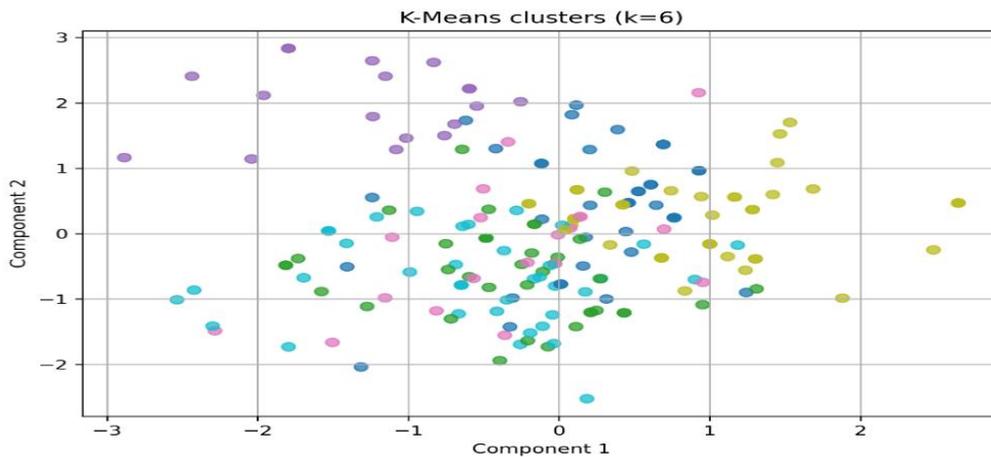


Figure 2. Cluster visualisation using K-means (k = 6).

There are six behavioural clusters presented in the plot on two main components. The distribution shows a distinct discrepancy in the consumer groups of engagement, personalisation perception, and privacy orientation.

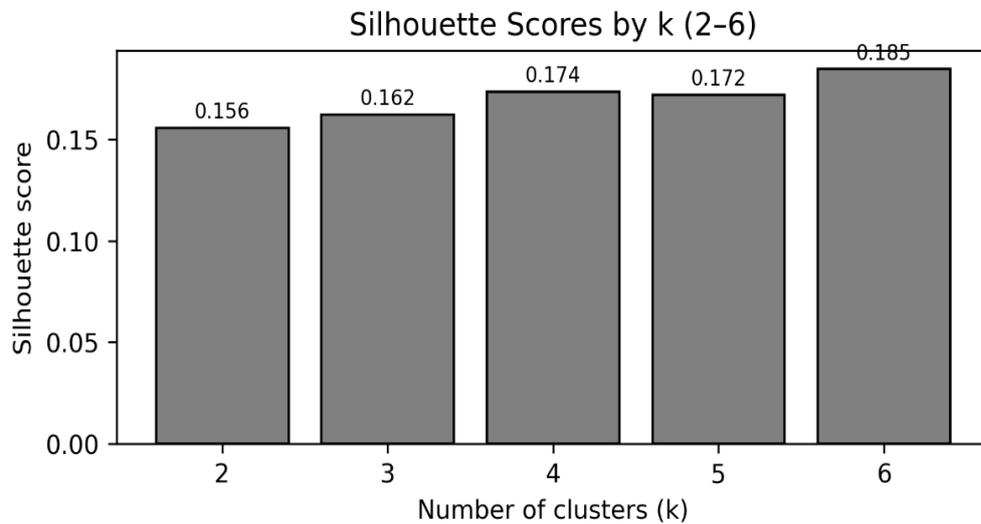


Figure 3. Silhouette Scores for Cluster Solutions (k = 2–6)

Silhouette comparison reveals that k = 6 gets the highest score (0.185), which is the best cluster structure to use in segmenting behavioural responses in this dataset

5.5 Regression Analysis

Personalisation significantly predicted Behavioural Response ($\beta = 0.773$, $p < 0.001$), explaining 47% variance ($R^2 = 0.466$). Higher perceived personalisation increased attention, interest and purchase intention, emphasising the importance of ethical, transparent data use.

Table 5. Relationship between Personalisation and Behavioural Response

Predictor	β (Unstandardised)	Std. Error	t / z-value	p-value	95% Confidence Interval
Intercept	0.714	0.212	3.37	0.001	[0.299, 1.129]
Personalisation Score	0.773	0.059	13.20	< 0.001	[0.658, 0.887]

Source: Computed using Python

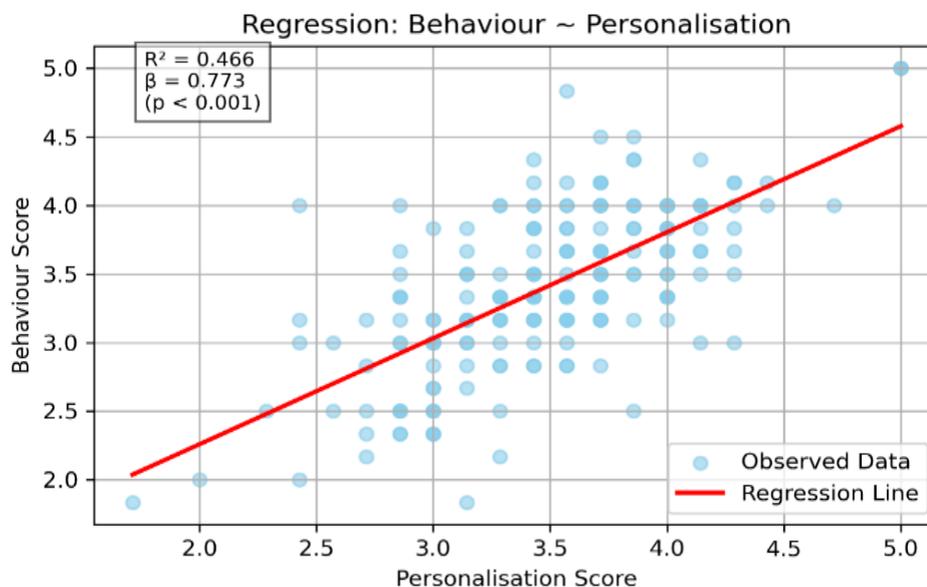


Figure 4. Regression Line between Personalisation and Behavioural Response

The scatter plot and the fitted regression line indicate that there is a clear positive correlation between personalisation and behavioural response. The scores of higher personalisation are linked to more engagement and interest, which is in line with the strong regression coefficient ($\beta = 0.773$). The positive inclination proves that the perceived relevance significantly increases the consumer responsiveness.

5.6 Correlation Analysis

Privacy Concern and Personalisation were also positively correlated moderately (Pearson $r = 0.540$; Spearman $\rho = 0.509$, $p = 0.001$), which is the privacy–personalisation paradox. Consumers react positively to relevant ads, and are, at the same time, increasingly conscious of privacy implications.

Table 6. Correlation between Privacy Concerns and Personalisation in Digital Advertising

Correlation Type	Coefficient (r / ρ)	p-value	Interpretation
Pearson (r)	0.540	< 0.001	Moderate positive linear correlation
Spearman (ρ)	0.509	< 0.001	Moderate positive correlation

Source: Computed using Python

6. Discussion

6.1 Insights from Findings

The results indicate that Indian consumers react differently to personalised advertising, reflected in six behavioural clusters ranging from highly engaged to privacy-driven or indifferent. The relevance of personalisation in digital communication is confirmed by a strong positive impact on behavioural response ($\beta = 0.773$). Simultaneously, all these advantages are accompanied by the issue of privacy, which creates the personalisation-privacy paradox. The involvement of privacy-sensitive users remains as long as transparency, control and ethical data practices are explicitly reported, demonstrating that successful digital advertising consists of the need to balance personalisation with the responsibility of dealing with data.

6.2 Practical Implications

The reason why segmented strategies are necessary is that consumer clusters do not react to personalisation in the same manner. Highly Engaged Seekers are reacting to powerful personalisation and dynamic creatives; Balanced Realists are reacting to transparent and consent-based messages. The Sceptical Observers require reduced frequency of advertisements and high levels of trust indicators; Privacy-Driven Consumers need to see an indication of privacy; Indifferent Viewers need to be exposed to utility-based advertising messages; Passive Consumers need to see low-personalisation awareness messages. To preserve trust, marketers will have to strengthen the privacy dashboard, enhance disclosures about the use of data, and implement permission-based tracking. The research adds the data of an emerging digital market where behavioural segmentation, personalisation and privacy sensitivity overlap. This way of segmenting into specific consumer groups demonstrates the fact that audiences of Indians online are not all the same and need different approaches. The results explain the use of relevance and privacy issues together to influence effectiveness in advertising.

6.3 Recommendations

The marketers are encouraged to use behavioural segmentation to develop personalised strategies for each cluster. Intrusiveness can be avoided with clear value exchange, data transparency, privacy as brand value, A/B testing, frequency limits and personalisation limits. Responsible data management and ethical personalisation facilitate long-term trust and loyalty.

6.4 Limitations

In its diversity, the sample is not quite representative of the Indian population. Causal conclusions are restricted by the cross-sectional design. The constructs that were analysed were only three, i.e. personalisation, privacy concern, and behavioural response and not other variables such as trust and perceived intrusiveness.

6.5 Future Research

More varied samples and other psychological variables should be used in future research. Changes in behaviour can be recorded using a longitudinal or experimental design. Comparisons across countries can enhance knowledge of cross-national disparity in the privacy-personalisation paradox.

7. Conclusion

This paper has discussed how the aspect of personalisation and privacy issues influences the response of consumer behaviour in the digital advertising environment in India. The results reveal that the Indian consumers are not a homogeneous group, but they make six different clusters of behaviour, which vary in their responses, engagement, and privacy orientation. Personalisation became a powerful indicator of the behavioural response, meaning that relevant and tailored content contributes greatly to attentional, interest and purchase intention. Meanwhile, the moderate positive correlation between personalisation and privacy concern illustrates the privacy-personalisation paradox, where consumers appreciate relevance and are more and more conscious of data risks as targeting gets increasingly more accurate. The findings indicate that privacy issues do not necessarily lessen the engagement, but rather, the effects depend on transparency, perceived controls, and ethical information procedures. Clarified brands that explain why they use the data, give the user control, and are better placed to maintain trust and remain engaged. Altogether, the paper underlines that successful digital advertising in India is dependent not just on sophisticated targeting technologies but on the need to balance between relevance and responsibility. Transparent data management, ethical personalisation and sensitivity to consumer privacy expectations will be vital to establishing long-term credibility and loyalty in a digitally-aware world that is growing more data-conscious.

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