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Article

Extracting Key Perceptual Factors Shaping Consumer Attitudes Toward AI-Enabled Advertising: An Exploration

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Abstract: In an ever-evolving digital ecosystem, artificial intelligence (AI) is establishing itself as a disruptive power in advertising, significantly transforming how organisations engage with customers. While programmatic advertising provides unparalleled levels of personalisation and precision in ad-targeting, it also poses challenging issues related to trust among consumers, perceived intrusion, emotional discomfort, and ethical data practice. Understanding the psychological underpinnings of consumer perception in this context is imperative, particularly in emerging markets such as India, where digital literacy is uneven and regulatory frameworks are still maturing. This study aims to extract and interpret the latent factors that shape Indian consumers' perceptions towards relevance of AI-enabled advertising. Employing a structured survey instrument, data were collected from 302 digitally active Indian respondents via a Likert-scale questionnaire. The data were analyzed using Exploratory Factor Analysis (EFA) through Principal Component Analysis (PCA) with Varimax rotation to reveal the underlying constructs governing consumer attitudes towards AI-enabled Advertisements. Nine distinct perceptual factors were identified, namely Perceived Privacy Intrusion, Perceived Ad-Relevance, Perceived Trustworthiness, Perceived Ad-Value, Perceived Privacy Assurance, Purchase Intent, Perceived Information Quality, Information Disclosure Discomfort and Click Willingness. Together, these factors provide a nuanced conceptual framework for understanding how Indian users engage with AI-generated advertisements at cognitive, affective, and behavioural levels. This study adds to the literature by finding and naming the factors for consumer perception in AI advertising, including implications for advertisers, and policymakers looking to create effective AI advertising ecosystem.

Keywords: Artificial Intelligence in Advertising; Indian Consumer Attitudes; Perceptual Factors; Exploratory Factor Analysis; Technology Acceptance Model; Consumer Privacy Concerns.

INTRODUCTION

The advertising industry is going through a paradigm shift, fuelled mostly by the widespread adoption of artificial intelligence (AI) technology. Advertising, formerly controlled by creativity and intuition, has now embraced computational precision, allowing businesses to deliver highly customised messages to specific consumers in real time. These advancements have improved targeting efficiency and transformed advertising into a predictive yet dynamic dialogue between consumers and algorithms. At the heart of this revolution is AI's ability to collect and analyse vast amounts of behavioural, contextual, and transactional data. Based on this information, AI systems may create advertising content that matches a user's tastes and preferences, search patterns, and even inferred emotional states(Forrest & Hoanca, 2015). While this has clearly increased the relevance and ad-engagement, it has also prompted important questions about privacy, data ethics, transparency, and the psychological consequences of algorithmic persuasion(Martin et al., 2017; Taylor, 2019; Vimalkumar et al., 2021).

1.1 The Rise of AI-enabled advertising

The dynamics of customer engagement, media personalization, and marketing analytics have changed in recent years because of the integration of artificial intelligence(AI) into advertising. Initially, started as a rule-based automated system that could send conditional messages or segment customers, these systems have now grown into complex ecosystem of personalization fueled by deep learning. AI is now able to identify patterns in user activity in real time, modify messaging aptly, and present contextually relevant ads on several platforms.

The transition from static campaigns to intelligent ad-distribution technologies marks an important milestone in advertising history. Machine Learning, Natural Language Processing(NLP) and predictive analytics enable marketers to move beyond standard demographic segmentation to Individual-level targeting (Rosenkrans & Myers, 2018). For instance, AI can now analyse not just what a consumer clicks on, but also when they are most likely to click, how long they spend viewing a specific content, and which psychological triggers boost the likelihood of purchase. These capabilities have transformed advertising campaigns, making them more responsive, data driven and consumer-focused than ever (Huang & Rust, 2021).

One of the most tangible benefits of AI in advertising is its potential to increase engagement through personalisation. AI-powered platforms analyse massive datasets—ranging from past browsing behaviour and geolocation data to facial expressions and mood indicators—to produce personalised and intuitive advertising experiences. As a result, customers are more likely to respond to commercials that appear "relevant" or "designed specifically" for them. This transition is most visible in industries like e-commerce, tourism, financial services, and entertainment, wherein adaptive content is now a norm. Platforms like Google Ads, Facebook Ads, and Amazon's recommendation engine use sophisticated algorithms to not only discover potential client categories, but also to deliver the correct message at the right time and in the appropriate format.

In practice, AI-driven ads may appear as personalized banners, chatbot interactions, voice assistant prompts, or content feeds adapted to the user's digital behaviour. These developments guarantee advertisers increased return on investment (ROI) and reduced cost of new customer acquisition; however, from the user's perspective, they raise worries about manipulation, psychological exhaustion, and surveillance capitalism (Zuboff, 2019).

1.2 The Indian Digital Landscape

India provides a very exciting environment that encourages technological growth. The country has experienced exceptional digital growth in the last decade. According to IAMAI and Kantar's Internet in India Report 2024 India has a remarkable internet user base of over 886 million people, expected to cross 900 million in 2025, with 86% those using over-the-top (OTT) music and video services(KANTAR; IAMAI, 2025). This digital expansion is followed by rising usage of social media platforms, e-commerce websites, and OTT services, all of which rely significantly on AI-driven advertising to monetise user engagement.

This digital surge has paved the way for AI-driven advertising advancements from global internet giants such as Google and Meta. Both platforms utilise artificial intelligence to maximise ad placement, adjust bidding in real-time, and tailor content based on expected user preferences. In India, for example, Meta's ad delivery system uses artificial intelligence to evaluate consumer sentiment in many languages, whereas Google's responsive search adverts dynamically change headlines and descriptions based on user search intent (Tran, 2024). These systems are efficient and generate billions of impressions per day, influencing customer behaviour on a massive scale.
However, as technology has advanced, several serious concerns have ascended, particularly with data privacy, customer trust, and the ethical limitations of algorithmic persuasion. While AI provides personalisation and efficiency, it also raises concerns about how customer data is acquired, stored, and used, particularly in a regulatory context that is constantly evolving. Many users are unaware of how AI systems work, what data they collect, and how they influence behaviour. In the absence of robust consumer education and comprehensive data protection laws (India's Digital Personal Data Protection Act was only recently introduced in 2023), consumers are often exposed to AI systems without meaningful consent or transparency. The absence of informed engagement poses distinct perceptual and ethical issues that must be discussed in the Indian socio-cultural context.

1.3 Gaps in Existing Research

The prior research on digital advertising has primarily focused on outcome factors like click-through rates, user engagement, and purchase intent. Despite being useful, such research frequently overlooks the underlying cognitive and emotional processes by which people evaluate AI-generated communication. Furthermore, these studies are majorly based on Western societies, where digital literacy is higher and privacy rules are more firmly established.

In India, there is a dearth of empirical research exploring how consumers perceive AI-enabled advertisements: what they find appealing, what they distrust, what makes them uncomfortable, and what leads to ad-skepticism. Such insights are critical not only for optimizing marketing strategies but also for informing policy frameworks and ethical standards in deployment of AI for Advertising.

1.4 Scope of the Present Study

The present study examines consumer behaviour, digital ethics, and the application of AI technology in advertising. Instead of testing hypotheses or forecasting behaviour using regression-based models, this study takes an exploratory approach, trying to identify the underlying structure of consumer perception towards AI-enabled advertising through statistical analysis of factors.

The central question guiding this research is: *What are the latent psychological dimensions that shape how Indian consumers perceive and respond to AI-enabled advertising?*

By extracting and interpreting these dimensions, the study aims to formulate a conceptually robust framework of consumer perception w.r.t AI-enabled Advertisements, that may support theoretical modelling for future research.

LITERATURE REVIEW

2.1 Technology Acceptance and AI Use

The Technology Acceptance Model (TAM), introduced by Fred Davis in 1989 remains one of the most widely applied frameworks in understanding user adoption of new technologies. At its core, TAM postulates that "two cognitive variables namely Perceived Usefulness (PU) and Perceived Ease of Use (PEOU), shape user attitudes and, consequently, behavioural intentions toward using any technology(F. Davis, 1987)." Over the years, TAM has been extended to contexts such as e-commerce, mobile applications, and intelligent systems, often incorporating additional constructs such as trust, perceived risk, and subjective norms (Carlos Martins Rodrigues Pinho & Soares, 2011; Lu et al., 2003; Venkatesh & Bala, 2008; Venkatesh & Davis, 2000). In AI-driven environments, PU manifests through constructs like decision-making support and informational value, while PEOU may be replaced or redefined through dimensions such as system interpretability or user autonomy (Dwivedi et al., 2021).

In this study, TAM is used as a theoretical backdrop to identify perceptual constructs such as informativeness and usefulness dimensions that may emerge naturally through exploratory factor analysis.

2.2 AI-Driven Personalization in Advertising

Although personalisation has long been a major theme in advertising, the advent of artificial intelligence has significantly altered the scope and level of detail of the idea. These days, AI systems can modify content in real time according to a user's past browsing habits, social media activity, purchasing patterns, and even their implied emotional state(Tucker, 2014). Predictive personalization, driven by machine learning algorithms, optimizes ad delivery by segmenting users not just by demographics but by dynamic behaviour. Research show that consumers are more expected to absorb personalized content, particularly when it reflects perceived relevance(Bleier & Eisenbeiss, 2015; Kim & Huh, 2017). On the other hand, Hyper-personalization might backfire when it exceeds a certain comfort level, resulting in emotions of manipulation or surveillance(Bang et al., 2019). This paradox, the concurrent attraction to and repulsion from AI personalization, highlights the complexities of consumer perception and lends support to an exploratory approach(Aguirre et al., 2016).

2.3 Consumer Trust and Perceived Transparency

The effectiveness and adoption of AI-enabled advertising are significantly influenced by trust. AI-enabled advertising forces users to believe the algorithm that creates the ad message in the background, in contrast to traditional advertising, which gets its credibility from message tone or brand reputation (Andrews et al., 2016). This requires faith in algorithmic fairness, system intent, and data management (Bleier & Eisenbeiss, 2015a). Studies show that perceived transparency i.e. "the extent to which a user understand why an ad is being shown, what data is used, and how it is used," can significantly enhance trust (Bleier & Eisenbeiss, 2015; Sirdeshmukh et al., 2002; Soh et al., 2013). When transparency is lacking, even relevant ads can evoke skepticism. Accordingly, constructs like data clarity, explainability, and control over data use are now integral to understanding consumer trust in AI systems(Diwanji et al., 2022). According to this study, trust and transparency will become crucial perceptual factors, especially in a culture like India where awareness of systems with algorithms is growing yet comparatively scarce.

2.4 Privacy Concerns and Data Ethics

Significant ethical concerns about data privacy, informed consent, and digital autonomy have been brought up by the implementation of artificial intelligence (AI) systems into digital advertising(Kumar & Suthar, 2024; Nill & Aalberts, 2014). Asymmetric exchanges of information arise due to the frequent use of opaque methods by AI systems to gather personal data, leaving users in the dark about what information is being gathered and how it is being monetized (Daems et al., 2019). The Consumer Privacy Concerns (CPC) framework (Lee et al., 2011; Malhotra et al., 2004) conceptualizes privacy anxiety as a multi-dimensional construct, encompassing control over personal information, awareness of data collection, and worries of secondary use. In the AI context, these concerns are intensified due to the non-transparent nature of algorithmic logic applied in personalised advertising (Zuboff, 2019). Furthermore, in India, where data protection legislation is still evolving, consumers may lack the legal literacy to evaluate AI practices critically.

These issues suggest that privacy concerns are not just regulatory matters; they are psychological dimensions likely to emerge in any factor structure related to consumer perception.

2.5 Psychological and Behavioural Reactions to AI enabled Advertising

Recent research has shown that customers' reactions to AI enabled advertising are not solely rational, but also intensely emotional and psychological. Users frequently express inconsistency, appreciating personalization while being concerned about the system's intelligence and reach (Aguirre et al., 2015; Brinson & Eastin, 2016; Chellappa & Sin, 2005). Emotions like discomfort, worry, and exhaustion are typical in high-frequency, tailored ad settings. These feelings can trigger reactance, a psychological defence mechanism against perceived manipulation. Furthermore, behavioural indications such as click avoidance, ad skipping, and the usage of ad blockers may be motivated by emotion rather than perceived relevance(Goldfarb & Tucker, 2012; Tucker, 2014).

These findings suggest that perceptual mapping of AI advertising interactions should incorporate both: emotional constructs such as discomfort or resistance, and cognitive evaluations like perceived usefulness and trust.

3. Research Objectives

Digital consumers' perceptions, responses, and delivery of advertisements are being redefined by artificial intelligence (AI). AI-driven advertising grants advantages like increased ad-personalization and improved decision-making, however, it also presents issues with trust, emotional discomfort, and data ethics(Aguirre et al., 2016). It is crucial to comprehend how customers understand these intricate experiences, especially in India, where digital engagement is growing, but AI system transparency is still low. Instead of relying on preconceived theoretical assumptions, this research uses an exploratory approach to identify the latent perceptual factors that influence consumer attitudes toward AI-enabled advertising.

The main objective of the current study is "*To extract and interpret the core perceptual factors that influence Indian consumers' responses to AI-enabled advertisements using exploratory factor analysis (EFA).*"

To fulfil the above-mentioned primary objective, the following are the secondary objectives that need to be achieved.

1. To identify meaningful clusters of perception (factors) from consumer survey data that reveal how users evaluate AI-enabled advertisements in terms of personalization, usefulness, emotional response, and data concerns.
2. To build a conceptual model based on extracted factors that may serve as a foundation for future research, ethical advertising strategies, and policy development in the Indian digital advertising ecosystem.

4. Rationale of the Study

The integration of AI in digital advertising has accelerated the transformation of consumer-brand interaction across global markets. However, as technical sophistication increases, so does the complexity of user interpretation, ethical scrutiny, and data governance (Wu & Wen, 2021). While AI-enabled ad-personalization has been lauded for its ability to enhance marketing precision, concerns regarding manipulation, psychological intrusion, and asymmetries in user knowledge is raised simultaneously (Qin & Jiang, 2019). Within this tension lies a critical research question- to examine not what AI systems do technically in the backdrop, but how the AI-enabled advertisements are perceived experientially by end users; particularly in under-researched, high-growth digital economies like India.

4.1 Conceptual Justification

Traditional studies on advertising success have gene rally focused on visible behavioural outcomes such a s click-
through rates, purchase intent and conversion metri cs(Azimi et al., 2012; Yoo, 2009). Despite their value,

these metrics frequently fall short of capturing the complex psychological factors that influences and precedes these behaviours. Particularly in AI-enabled contexts, where content is auto-curated, and decision pathways are algorithmically mediated, consumer perceptions, emotions, and cognitive appraisals play a central role (G. Chen et al., 2019).

Moreover, many existing theoretical models, such as TAM, UTAUT, or even more recent extensions integrating trust or privacy concerns, impose predefined constructs on user experience (Wang et al., 2023). While these models have predictive utility, they risk overlooking the emergent and context-dependent dimensions that naturally arise from users' personal interactions with AI-generated advertising. This study adopts an exploratory strategy, diagnosing that consumers construe AI-generated information through complex cognitive-emotional frameworks that shape their perceptions and reactions. Given this sensitive knowledge, exploratory factor analysis (EFA) is utilised as a methodological option that is particularly well-suited to revealing the latent dimensions buried within perceptual data. EFA provides a solid foundation for future theoretical models to be constructed and refined, as well as the ability to empirically detect underlying structures that may not be visible at first glance.

4.2 Contextual Relevance: The Indian Digital Landscape

India, with one of the fastest-growing internet user bases, estimated to cross 900 million by 2025, India stands at the forefront of AI implementation in advertising. The country offers a particularly fascinating setting for this kind of research. Domestic and global platforms alike employ AI systems to deliver curated content, drive engagement, and influence consumer behaviour. Nevertheless, this digital advancement is unfolding in a regulatory environment still in transition, where the recently introduced Digital Personal Data Protection Act (2023) is only beginning to formalize user rights, consent protocols, and data usage limits (KANTAR; IAMAI, 2025). Moreover, digital literacy in India remains uneven. Many users interact with AI-driven advertisements without fully understanding the data structures that underlie them, even though urban, educated consumers may have a basic understanding of algorithmic personalization. Perceptual analysis is not only an academic endeavour but also a socio-ethical necessity because of this information asymmetry, which breeds mistrust, confusion, or emotional dissatisfaction.

Understanding how Indian consumers internalize and interpret AI-enabled advertising is thus vital for Marketers - who must balance targeting efficiency with user comfort and trust; Policymakers - who require data-driven insights into user sentiment to guide ethical AI deployment; and Technologists and platform designers - who must reconcile system performance with transparency, fairness, and psychological acceptability.

4.3 Empirical Gap and Research Contribution

A thorough review of the digital advertising literature reveals a significant dearth of empirical studies concentrating on the latent psychological elements of perceived ad relevance of AI-enabled advertising in India. While numerous conceptual articles and global surveys have raised concerns about *personalization* (how ads are tailored to individuals) (Chandra et al., 2022; Lee et al., 2011; Sahni et al., 2018); *Surveillance* (being watched or tracked by technology) (Martin et al., 2017; Rapp et al., 2009; Zuboff, 2019) ; and *trust* (whether consumers believe or accept the use of AI in privacy advertising) (Culnan & Armstrong, 1999; Huh et al., 2020; Reyes et al., 2025; Sirdeshmukh et al., 2002; Soh et al., 2013); very few have employed rigorous statistical techniques like factor analysis to identify the structural underpinnings of consumer perception in this domain. This study, therefore, makes a methodological and conceptual contribution by (i) applying exploratory factor analysis to extract perceptual factors without imposing pre-existing theoretical constraints and (ii) developing a comprehensive measurement instrument based on validated items and adapting to the Indian context. By doing so, the study provides a first-principles framework upon which future research, regulatory models, and ethical guidelines can be constructed.

RESEARCH METHODOLOGY

In keeping with the exploratory and constructivist orientation of the research, a quantitative data collection strategy was employed, supported by exploratory factor analysis (EFA) to uncover latent variable structures.

5.1 Research Design

The study is grounded in a quantitative research paradigm, which seeks to derive generalizable insights through objective measurement, statistical analysis, and replicable methods. While the underlying research orientation is exploratory, it emphasizes quantifiable constructs, structured instruments, and statistical rigour in construct identification(Joseph F. Hair Jr. et al., 2014). The exploratory research design is particularly suited to domains where theoretical consensus is absent or where latent constructs are suspected to exist but have not been systematically mapped (Hair et al., 1998). An exploratory research design is methodologically appropriate given the nascent nature of AI-enabled advertising and the insufficient understanding of consumers' perception towards such intelligent ads in the Indian context.

5.2 Instrument Design

The research instrument consisted of a structured, self-administered questionnaire comprising both demographic questions and perceptual items. The questionnaire was divided into sections comprising *Socio-demographic variables* (age, gender, education, occupation, marital status, AI exposure frequency) and a set of 55 Likert-scale items measuring *perceptual dimensions* related to consumers' perceived ad-relevance towards AI-enabled advertising. These items were adapted from validated scales used in prior studies on digital personalization, consumer trust, privacy concerns, data ethics, emotional discomfort, and behavioural responses (Dinev & Hart, 2006a; Laczniak & Muehling, 1993; MacKenzie & Lutz, 1989; Malhotra et al., 2004; Roy et al., 2017; Soh et al., 2013; Venkatesh et al., 2003; Wang et al., 2023). The Items were adapted and revised to reflect the Indian digital user context and pre-tested for language clarity and interpretability. The questionnaire was rigorously reviewed and validated by experienced researchers and academicians specializing in the fields of marketing and advertising. All perceptual items were measured on a five-point Likert scale ranging from 1 ("Strongly Disagree") to 5 ("Strongly Agree"), enabling interval-level analysis for factor extraction.

5.3 Sampling

Given the exploratory nature of the study, a non-probability convenience sampling strategy was adopted to capture a diverse but accessible cohort of Indian digital users. The inclusion criteria required the participants to be Indian nationals aged 18 years or older; possess regular exposure to AI-enabled advertisements (e.g., Google Ads, YouTube recommendations, Instagram promotions) and be comfortable completing an online survey in English.

5.4 Data Collection Procedure

Platforms like *Zoho Survey* and *Google Forms* was utilised to distribute the survey online, and it was shared via professional forums, university groups, email networks, and social media. All participants gave their informed consent prior to accessing the questionnaire, and participation was entirely voluntary. No personally identifiable information was gathered; even giving their *name* was optional, and anonymity was guaranteed. Response quality was tracked in real-time during the 12-week data collection period between April-July 2023. The final analysis did not include the entries with missing values or inconsistent/unengaged responses (e.g., the same ratings for every item). The dataset was screened to ensure compliance with the assumptions of multivariate analysis. Prior to conducting data analysis, the missing values were handled through case wise deletion.

6. Data Analysis

The filled-in responses were received from 350 respondents, out of which 48 responses were incomplete, leading to their removal from the study. After elimination of these half-finished or unengaged responses a total of 302 responses were analysed in this pilot study, which aligns with accepted sample size norms for factor analysis, particularly where the variable-to-response ratio is 1:5 or more. As per Hair, *"the minimum is to have at least five times as many observations as the number of variables to be analyzed"* for Exploratory Factor Analysis (Hair et al., 1998). While this pilot sample does not claim national representativeness, it provides statistically adequate grounds for exploratory factor extraction (Table 1).

Table 1: Demographic Profile of Respondents

Variables		Frequency	Percentage
Gender	Female	110	36.4
	Male	192	63.6
	Total	302	100
Age Group (in years)	18-25	190	62.9
	26-35	98	32.5
	36-45	10	3.3
	46-55	4	1.3
	55 and above	0	0
	Total	302	100
Educational Qualifications	Matriculation (10th)	4	1.3
	Under-Graduate (UG)	150	49.7
	Post-Graduate (PG)	108	35.8
	PhD and other higher studies	40	13.2
	Total	302	100
Occupation	Student	258	85.4
	Employed (Government/Private)	36	11.9
	Searching for Jobs	2	0.7
	Professionals (Lawyer/Teacher/Doctor etc.)	6	2.0
	Total	302	100
Marital Status	Unmarried	268	88.7
	Married	34	11.3
	Total	302	100

(Source: Authors' Compilation)

6.1 Suitability of Data for Factor Analysis

To assess whether the dataset is suitable for factor analysis, two preliminary tests are commonly applied, prior to extraction: the *Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy* and *Bartlett's test of sphericity*. These tests help determine whether the relationships among variables are strong enough to justify a factor analysis. The KMO statistic evaluates the proportion of variance among variables that might be common variance. According to Kaiser, a minimum acceptable KMO value is 0.5 (Cerny & Kaiser, 1977). Building on this, (Hutcheson & Sofroniou, 1999) categorized KMO values as follows: 0.5 to 0.7 indicates *mediocre* adequacy, 0.7 to 0.8 is considered *good*, 0.8 to 0.9 is regarded as *great*, and values above 0.9 are deemed *excellent*. *Bartlett's test*, on the other hand, evaluates whether the correlation matrix significantly differs from an identity matrix, implying that variables are interrelated. For this test to support the use of factor analysis, the significance level should be below 0.05, indicating that the data exhibits sufficient correlations to proceed with the analysis (Tobias & Carlson, 1969).

In this study, the *Kaiser-Meyer-Olkin* (KMO*)* measure of sampling adequacy yielded a value of 0.795 exceeding the minimum threshold of 0.50, This suggests that the responses were sufficiently dense for factor analysis and likely to yield distinct and reliable components(Cerny & Kaiser, 1977). *Bartlett's Test of Sphericity* was highly significant, indicating that the item correlation matrix was suitable for factor extraction(Tobias & Carlson, 1969) (see Table 2).

Table2: KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0.795
Bartlett's Test of Sphericity	Approx. Chi-Square χ^2	13791.289
	df	1275
	Sig. (p)	0.000

(Source: Authors' Compilation)

6.2 Factor Extraction and Retention Criteria

The primary statistical technique employed was *Exploratory Factor Analysis* (EFA), which used *Principal Component Analysis* (PCA) as the extraction method and *Varimax rotation* as the rotation technique. This approach facilitates the identification of uncorrelated, orthogonal factors that reflect distinct perceptual themes within the data. The initial communalities for all items are set to 1.0 because PCA is predicated on the idea that all variances in the observed variables are initially regarded as common. As presented in Table 3, the communalities for all 51 retained items ranged from 0.501 to 0.865, well within acceptable psychometric thresholds. According to standard guidelines given by Hair et al. (1998), the communality values above 0.50 are considered indicative of sufficient shared variance between observed variables and the underlying factors. This suggests that the extracted components capture a substantial proportion of variance in each individual item.

Following factor extraction, the communalities indicate the proportion of variance in each item that is explained by the retained factors. Several items exhibited notably high communalities, reflecting strong representation of their underlying latent constructs. These include Q_25 ("Information conveyed in the AI-enabled Intelligent Advertisements shown to me are truthful") with a communality of 0.864, Q_19 ("Online companies should devote more time and effort into preventing unauthorized access to consumers' personal information") at 0.841, Q_18 ("Computer databases that contain consumers' personal information should be protected from unauthorized access, irrespective of the cost") at 0.825, Q_41 ("I am willing to consider the ad-conveyed information when making purchase-related decisions") at 0.824, Q_20 ("Online companies should never share consumers' personal information without authorization") at 0.796, Q_31 ("Information conveyed in the AI-enabled Intelligent Advertisements are complete") at 0.790, and. These high values suggest that these items are highly representative of their respective factors.

Even the items with relatively lower communalities, such as Q_53 ("I am concerned about what digital advertisers might do with my browsing history") at 0.478, Q_54 ("I am concerned that digital advertisers are collecting too much information about me") at 0.543, and Q_51 ("I believe that my privacy is seriously threatened by use of AIeIA for personalized advertising") at 0.536, were close to or above the commonly accepted minimum threshold of 0.50. Because of their theoretical importance and distinctive contribution to the dimensionality of the construct, these items were kept. The structural integrity and reliability of the extracted factors are confirmed by the consistently high communalities across most items.

Following the evaluation of the *total variance explained* (Table 4), the analysis revealed that the observed variables could be grouped into *nine* distinct components, each capturing a unique dimension of consumer perception toward AI-enabled advertising.

Table 3: Communalities

Item Number	Initial	Extraction	Item Number	Initial	Extraction	Item Number	Initial	Extraction
Q_2	1.000	.670	Q_21	1.000	.762	Q_39	1.000	.782
Q_4	1.000	.569	Q_22	1.000	.641	Q_40	1.000	.765
Q_6	1.000	.668	Q_24	1.000	.758	Q_41	1.000	.824
Q_7	1.000	.500	Q_25	1.000	.864	Q_42	1.000	.743
Q_8	1.000	.786	Q_26	1.000	.737	Q_43	1.000	.709
Q_9	1.000	.671	Q_27	1.000	.729	Q_44	1.000	.550
Q_10	1.000	.786	Q_28	1.000	.787	Q_45	1.000	.719
Q_11	1.000	.746	Q_29	1.000	.729	Q_46	1.000	.575
Q_12	1.000	.658	Q_30	1.000	.694	Q_47	1.000	.668
Q_13	1.000	.746	Q_31	1.000	.790	Q_48	1.000	.695
Q_14	1.000	.744	Q_32	1.000	.740	Q_49	1.000	.694
Q_15	1.000	.672	Q_33	1.000	.727	Q_50	1.000	.767
Q_16	1.000	.685	Q_34	1.000	.748	Q_51	1.000	.536
Q_17	1.000	.682	Q_35	1.000	.707	Q_52	1.000	.565
Q_18	1.000	.825	Q_36	1.000	.757	Q_53	1.000	.478
Q_19	1.000	.841	Q_37	1.000	.695	Q_54	1.000	.543
Q_20	1.000	.796	Q_38	1.000	.699	Q_55	1.000	.707

Extraction Method: Principal Component Analysis

(Source: Authors' Compilation)

Table 4: Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	11.770	23.079	23.079	11.770	23.079	23.079	7.038	13.800	13.800
2	7.598	14.898	37.978	7.598	14.898	37.978	6.379	12.509	26.309
3	4.270	8.373	46.351	4.270	8.373	46.351	4.927	9.660	35.969
4	3.544	6.950	53.301	3.544	6.950	53.301	4.518	8.859	44.828
5	2.417	4.740	58.041	2.417	4.740	58.041	3.940	7.726	52.555
6	1.968	3.859	61.900	1.968	3.859	61.900	3.502	6.867	59.422
7	1.634	3.204	65.104	1.634	3.204	65.104	2.076	4.070	63.492
8	1.425	2.795	67.899	1.425	2.795	67.899	1.939	3.802	67.294
9	1.301	2.550	70.449	1.301	2.550	70.449	1.609	3.155	70.449
10	1.182	2.317	72.766						
11	.991	1.943	74.709						
12	.964	1.890	76.600						
13	.901	1.767	78.367						
14	.760	1.489	79.856						
15	.703	1.378	81.234						
16	.667	1.308	82.541						
17	.634	1.244	83.785						
18	.591	1.159	84.944						
19	.566	1.110	86.054						
20	.545	1.069	87.123						
21	.509	.998	88.121						
22	.466	.914	89.035						
23	.452	.886	89.921						
24	.409	.802	90.723						
25	.369	.724	91.446						

26	.352	.691	92.137						
27	.328	.644	92.780						
28	.323	.634	93.414						
29	.296	.581	93.995						
30	.280	.549	94.544						
31	.263	.517	95.061						
32	.250	.491	95.551						
33	.214	.419	95.970						
34	.200	.392	96.363						
35	.195	.383	96.745						
36	.183	.360	97.105						
37	.170	.333	97.438						
38	.156	.305	97.744						
39	.145	.284	98.028						
40	.132	.258	98.285						
41	.122	.240	98.526						
42	.115	.226	98.752						
43	.111	.218	98.970						
44	.096	.189	99.158						
45	.089	.175	99.334						
46	.081	.159	99.493						
47	.071	.138	99.632						
48	.066	.129	99.761						
49	.046	.089	99.850						
50	.041	.080	99.930						
51	.035	.070	100.000						

Extraction Method: Principal Component Analysis

(Source: Authors' Compilation)

6.3 Rotated Component Matrix:

The Rotated Component Matrix provides detailed insights into the variable loadings on each of the nine extracted factors. Factor loadings above 0.50 are considered strong. This step facilitated clearer identification and labelling of the factors, aiding in the development of a structured and interpretable factor solution. The Rotated Component Matrix Table (Table 5) shows that most items demonstrated high loadings on a single factor with no cross-loading, indicating excellent construct purity and structural clarity.

Table 5: Rotated Component Matrix

	Component								
	1	2	3	4	5	6	7	8	9
Q_50	.817								
Q_55	.811								
Q_48	.796								
Q_47	.774								
Q_49	.763								
Q_45	.756								
Q_46	.738								
Q_52	.727								
Q_51	.701								
Q_54	.655								
Q_53	.643								
Q_44	.630								
Q_10		.861							
Q_8		.857							
Q_14		.820							
Q_11		.805							
Q_13		.766							
Q_6		.734							
Q_22		.643							
Q_7		.598							
Q_12		.591							
Q_9		.567							

Q_25			.887						
Q_24			.821						
Q_29			.814						
Q_28			.663						
Q_26			.620						
Q_27			.567						
Q_35			.543						
Q_33				.834					
Q_34				.778					
Q_38				.752					
Q_37				.672					
Q_36				.671					
Q_19					.859				
Q_18					.837				
Q_20					.823				
Q_21					.763				
Q_17					.740				
Q_40						.739			
Q_39						.732			
Q_42						.722			
Q_41						.704			
Q_43						.599			
Q_32							.786		
Q_31							.552		
Q_30							.544		
Q_15								.692	
Q_16								.629	
Q_2									.666
Q_4									.541

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 9 iterations.

(Source: Authors' Compilation)

Since exploratory factor analysis can occasionally yield slightly varied rotated solutions owing to differences in convergence criteria, computational algorithms, or random starting points, the Component Transformation Matrix (Table 6) ensures methodological transparency by providing a reproducible mathematical record of how the original factor axes were transformed to achieve a simpler, more interpretable structure (Watkins, 2018).

Table 6: Component Transformation Matrix

Component	1	2	3	4	5	6	7	8	9
1	-.142	.559	.492	.439	-.186	.363	.200	-.126	.105
2	.909	.068	.148	.122	.336	.082	.059	.086	-.034
3	.097	.744	-.392	-.507	-.014	-.011	-.042	-.068	.142
4	-.353	.207	.191	.044	.810	-.254	-.022	.268	.024
5	-.094	-.098	-.530	.255	.204	.675	-.024	.290	.229
6	-.072	-.220	.271	-.595	.160	.400	.571	-.080	.005
7	.046	-.051	.400	-.288	-.231	.084	-.422	.564	.443
8	.029	.083	-.164	.132	-.262	-.320	.634	.613	-.012
9	.051	-.142	-.064	.121	.077	-.266	.218	-.341	.848

"Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

(Source: Authors' Compilation)

6.4 Summary of Extracted Factors

The factor analysis produced a robust and interpretable structure, summarizing multi-dimensional consumer perceptions and behavioural orientations toward AI-enabled advertising. These dimensions reflect a nuanced interplay of cognitive, affective, and evaluative factors underlying technology adoption and marketing receptivity in the AI-enabled advertising context. The EFA revealed *nine* well-defined and interpretable factors, each capturing a unique dimension of consumer perceptions toward AI-enabled advertising. These factors represent the multi-faceted attitudes, emotional responses, and behavioural intentions of Indian consumers in the context of AI-driven marketing communications. This suggests that the constructs identified through Principal Component Analysis (PCA) adequately represent the underlying structure of consumer perceptions toward AI-enabled advertising. The high level of shared variance across the instrument's items further validates the scale's suitability for subsequent interpretation and naming of latent dimensions, grounded in the Technology Acceptance Model (TAM) and related theories of digital trust, user attitude, and perceived usefulness. Following rotation using the Varimax method with Kaiser Normalization, the retained components were evaluated and named based on theoretical alignment with the Technology Acceptance Model (TAM) and its extensions (e.g., TAM2, UTAUT, Trust-based TAM) and other related theories (Carlos Martins Rodrigues Pinho & Soares, 2011; F. Davis, 1987; Lu et al., 2003; Venkatesh & Bala, 2008; Venkatesh & Davis, 2000). A comprehensive cross-referencing with existing literature and an iterative content analysis of the items were used to thematically label each factor (Table 7).

Table 7: Summary of Extracted Factors and Thematic Interpretations

Factor No.	Factor Label	Description	Item numbers
1	*Perceived Privacy Intrusion*	Refers to consumers' concerns and discomfort about the potential invasion of their privacy when AI-driven ads access and use their personal data.	Q_50, Q_55, Q_48, Q_47, Q_49, Q_45, Q_46, Q_52, Q_51, Q_54, Q_53, Q_44
2	*Perceived Ad-Relevance*	Represents the degree to which consumers feel the ads they encounter are meaningful, personalized, and aligned with their needs and interests.	Q_10, Q_8, Q_14, Q_11, Q_13, Q_6, Q_22, Q_7, Q_12, Q_9
3	*Perceived Trustworthiness*	The extent to which consumers believe that the AI-enabled ads are reliable, truthful, and provide accurate information.	Q_25, Q_24, Q_29, Q_28, Q_26, Q_27, Q_35,
4	*Perceived Ad-Value*	A combined perception of the emotional (hedonic) and functional (utilitarian) value derived from the AI-enabled ads in terms of enjoyment and usefulness.	Q_33, Q_34, Q_38, Q_37, Q_36
5	*Perceived Privacy Assurance*	The assurance that personal information is safeguarded and properly handled by advertisers, reducing the risk of privacy breaches.	Q_19, Q_18, Q_20, Q_21, Q_17

6	*Purchase Intent*	The likelihood of a consumer making a purchase decision based on exposure to AI-enabled advertisements and their perceived influence on buying behavior.	Q_40, Q_39, Q_42, Q_41, Q_43
7	*Perceived Information Quality*	The degree to which consumers perceive the information provided in the ad as relevant, clear, and useful for decision-making.	Q_32, Q_31, Q_30
8	*Perceived Information Disclosure Discomfort*	The psychological unease consumers feel when asked to share personal information, particularly in situations where the request for data is deemed excessive, irrelevant, or unnecessary.	Q_15, Q_16
9	*Click Willingness*	The likelihood that a consumer will click on an ad, reflecting their interest in engaging with the advertisement or exploring the product/brand further.	Q_2, Q_4

(Source: Authors' Compilation)

Each of these nine factors group together a set of interrelated items with strong internal correlations, thus revealing latent perceptual constructs among Indian digital consumers. The factor labels were developed through a qualitative interpretation of high-loading items and reflect the dominant psychological and behavioural themes underpinning each dimension.

6.5 Reliability Analysis

After performing exploratory factor analysis (EFA), reliability analysis is critical for evaluating the internal consistency of the obtained constructs. While EFA helps to reveal the underlying factor structure and group related items, it does not confirm that these items consistently measure the intended latent constructs (Hair et al., 1998; Vaske et al., 2017). Reliability analysis, commonly measured using Cronbach's Alpha, guarantees that the items within each component are coherent and stable, confirming the measurement model's trustworthiness (Tavakol & Dennick, 2011). High reliability shows that the factor is well-defined and the items measure the same underlying concept, which is required to make reliable conclusions from the data (Cortina, 1993; Vaske et al., 2017).

Table 8: Reliability Statistics

Factor Number	Factor Name	Cronbach's Alpha	N of Items
FAC_1	*Perceived Privacy Intrusion*	.923	12
FAC_2	*Perceived Ad-Relevance*	.921	10
FAC_3	*Perceived Trustworthiness*	.913	7
FAC_4	*Perceived Ad-Value*	.886	5
FAC_5	*Perceived Privacy Assurance*	.885	5
FAC_6	*Purchase Intent*	.869	5
FAC_7	*Perceived Information Quality*	.712	3
FAC_8	*Perceived Information Disclosure Discomfort**	.702	2
FAC_9	*Click Willingness**	.661	2

(Source: Authors' Compilation)

* The factors "*Perceived Information Disclosure Discomfort*" (FAC_8) and "*Click Willingness*" (FAC_9), each comprising only two items, recorded Cronbach's Alpha values of 0.702 and 0.661, respectively. While the former meets the conventional threshold for internal consistency, the latter, though slightly below 0.70, is considered acceptable in the context of exploratory research. Despite diverging from the typical recommendation of *three items per factor*, both constructs are retained based on their strong item loadings, conceptual clarity, and empirical relevance to the research context. Two-item constructs are considered acceptable in exploratory factor analysis when they demonstrate adequate internal correlation and conceptual alignment, especially in early-stage or pilot studies (Eisinga et al., 2013; Worthington & Whittaker, 2006).

7. Interpretation of Results

The results of the exploratory factor analysis (EFA) provided valuable insights into the components influencing Indian consumers' perception towards AI-enabled advertising. The current study discovered nine distinct factors, each indicating different aspects of consumer interaction with AI-enabled advertising. Cronbach's alpha measures the internal reliability of these constructs, which demonstrates excellent consistency among the items within each construct.

7.1 Factor Extraction Results and Theoretical Contextualization

7.1.1 Factor 1: Perceived Privacy Intrusion

Perceived Privacy Intrusion, represents reservations regarding privacy and trust in AI-enabled advertising. This factor emerged from items that measure consumer perceptions of how data requirements for AI-enabled advertising might invade personal privacy. With a Cronbach's alpha value of .923, this factor demonstrates high internal consistency, indicating that the items collectively assess a single, coherent construct. This factor is consistent with *Privacy Calculus Theory*, which postulates that individuals assess the benefits of online services against potential privacy risks (Smith et al., 1996). Similarly, *Trust-enhanced TAM (Harrison McKnight et al., 2002)* emphasizes the role of trust in moderating consumer attitudes toward digital technologies, which is evident in this construct. Consumers' concerns regarding data privacy are critical for advertisers to address. Privacy assurance in AI-enabled advertising is central to fostering trust, which in turn can impact consumer willingness to engage with ads. This factor's high reliability indicates that privacy concerns are a significant predictor of consumer behaviour in the digital advertising context, aligning with previous research that highlights the centrality of privacy in the acceptance of digital technologies (Featherman & Pavlou, 2003).

7.1.2 Factor 2: Perceived Ad-Relevance

Perceived Ad-Relevance represents consumers' perceptions of the relevance of AI-driven advertisements to their needs and preferences. This factor, with a Cronbach's alpha of .921, also demonstrated excellent reliability. It aligns with the Perceived Usefulness (PU) construct from TAM, which suggests that the more useful individuals perceive a technology to be, the more likely they are to accept and engage with it (F. D. Davis, 1989). In the context of advertising, relevance is a key determinant of perceived usefulness, as personalized and relevant ads are seen as providing more value. This finding confirms the growing importance of personalization in digital marketing, where consumers expect tailored content that speaks directly to their interests. The results underscore the importance for advertisers to develop algorithms that optimize ad relevance, as irrelevant ads lead to consumer disengagement (Bleier & Eisenbeiss, 2015).

7.1.3 Factor 3: Perceived Trustworthiness

Perceived Trustworthiness emerged as a significant factor reflecting consumer trust in AI-enabled advertising platforms. With a Cronbach's alpha of .913, this construct is highly reliable. It is grounded in both the Trust and Perceived Trustworthiness dimensions of TAM extensions, particularly the work of Featherman & Pavlou (2003) and McKnight et al. (2002), which emphasize trust as a key determinant of technology acceptance. This factor highlights the essential role of trust in shaping consumer perceptions about AI-enabled advertising.
To maintain and develop trust, advertisers must ensure that AI systems are transparent, virtuous, and secure. Building trust is critical for driving long-term consumer engagement with AI-powered marketing, especially given the growing worries about data protection and abuse.

7.1.4 Factor 4: Perceived Ad-Value

Perceived Ad-Value considers both the hedonic and utilitarian features of AI-enabled ads, representing how consumers perceive the value it brings. With a Cronbach's alpha of.886, this component has excellent internal consistency. It is closely related to TAM's Perceived Usefulness (PU) as well as UTAUT2 components, including Hedonic Motivation and Perceived Usefulness (Venkatesh et al., 2012).

Consumers are more inclined to engage with advertisements that they deem useful, whether for amusement, education, or utility. This aspect emphasises that advertisements can bring value in two ways: *functionally* (useful products or services) and *emotionally* (entertainment or delight) (Van-Tien Dao et al., 2014). To boost engagement, advertisers should concentrate on developing a system that generates AI-enabled ads which provide both emotional and informational value.

7.1.5 Factor 5: Perceived Privacy Assurance

Perceived Privacy Assurance refers to how consumers perceive the protection of their personal information in AI-enabled advertising. This factor had a Cronbach's alpha of.885, indicating a high level of reliability (Bansal et al., 2015). This construct builds on the Perceived Security and Perceived Privacy dimensions in TAM extensions, highlighting the role of privacy assurances in fostering consumer trust and willingness to engage (Featherman & Pavlou, 2003).

Privacy concerns remain one of the major impediments to digital advertising acceptability. Thus, marketers must provide unambiguous privacy assurances and data protection procedures. Ensuring privacy is not only a legislative duty but also a strategic advantage in fostering consumer trust and participation (Dinev & Hart, 2006b).

7.1.6 Factor 6: Purchase Intent

Purchase Intent reflects consumers' likelihood of purchasing a product or service after being exposed to AI-driven ads. With a Cronbach's alpha of .869, this factor demonstrates strong reliability. It is grounded in the Behavioural Intentions construct from TAM, which suggests that perceived usefulness and ease of use influence consumers' intentions to act (Davis, 1989). This component is critical for advertisers since it has a direct correlation with sales performance. AI advertisements that effectively affect buying intentions can yield a high return on investment. This emphasises the necessity of targeting ads that are relevant to consumer tastes and requirements.

7.1.7 Factor 7: Perceived Information Quality

Perceived Information Quality refers to how customers assess the relevance, accuracy, clarity, and usefulness of information offered in advertisements powered by artificial intelligence. With a Cronbach's alpha of .712, this component is moderately reliable. It draws on constructs from the Technology Acceptance Model 3 (TAM3), particularly Perceived Information Quality and Output Quality, which emphasize the role of high-quality information in enhancing decision-making and reducing cognitive effort (Venkatesh & Bala, 2008).

In the context of AI-enabled advertising, *perceived information quality* influences customer trust and engagement. Advertisements that convey factual, clear and relevant information are more likely to be perceived as credible and beneficial (Davies, 2001; Lou & Yuan, 2019).

7.1.8 Factor 8: Perceived Information Disclosure Discomfort

Perceived Information Disclosure Discomfort reflects consumers' apprehension regarding the collection, usage, and exposure of personal information in AI-enabled advertising. This factor, with a Cronbach's alpha of .702, indicates moderate reliability. It is informed by Privacy Calculus Theory and the perceived risk dimensions found in extended TAM frameworks, which suggest that consumers weigh the benefits of personalization against the perceived risks to their privacy (Dinev & Hart, 2006b; Xu et al., 2025).

Customers experience discomfort when they believe the risks outweigh the advantages, which may make them reluctant to use platforms that use these kinds of data acquisition methods (Meng & Liu, 2025). To enhance consumer receptivity, marketers must address transparency in data use and ensure that AI systems operate within ethically sound and privacy-conscious frameworks to address perceived discomfort with information disclosure (Tadelis & Zettelmeyer, 2015).

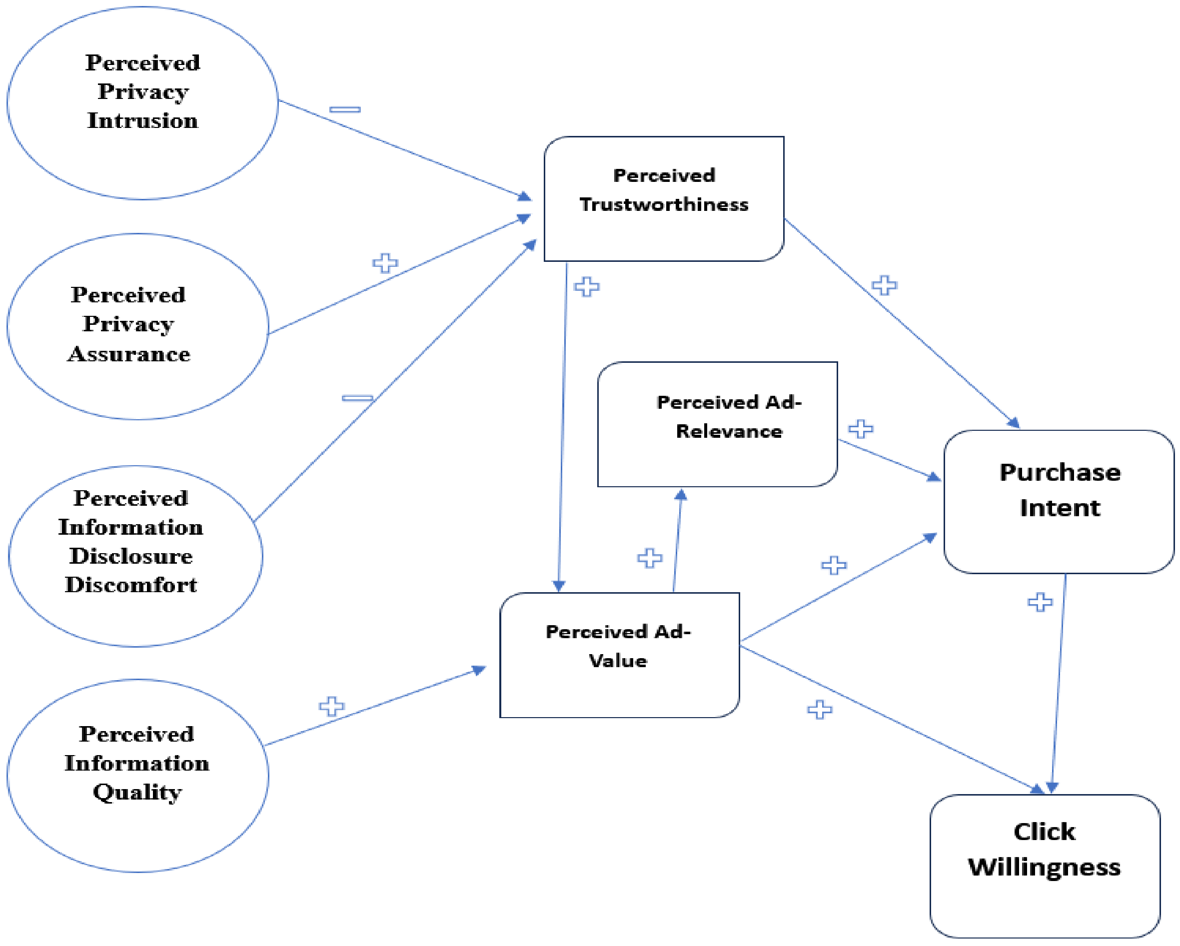
7.1.9 Factor 9: Click Willingness

Click Willingness reflects consumers' likelihood of clicking on any AI-driven ad. With a Cronbach's alpha value of .661, this factor shows a relatively lower reliability compared to the other factors, but it is still useful for understanding consumer behavior. This construct is derived from *Behavioural Intention* in TAM, which suggests that the likelihood of acting (clicking) is influenced by perceived ad effectiveness and trust (Bleier & Eisenbeiss, 2015). Click willingness is a direct measure of ad-effectiveness and an essential metric for digital advertising success. Advertisers can use this factor to assess the engagement potential of AI powered ads and optimize campaigns to encourage more clicks (H. Chen, 2024; Fulgoni & Mörn, 2009).

7.2 Conceptual Model Development

Based on the explanatory insights drawn from the extracted factors, a conceptual model is proposed to represent the perceptual framework that underpins Indian consumers' responses to AI-enabled advertising (Figure 1). This conceptual framework also serves as an initial step toward the development of a broader theoretical understanding and provides a basis for future empirical research in AI-enabled advertising research. Motivated by the Technology Acceptance Model (TAM) and its extensions, the diagram delineates how external variables, such as perceived privacy intrusion, privacy assurance, and information disclosure discomfort, exert positive(+) or negative(-) influences on perceived trustworthiness. Trustworthiness, in turn, along with perceived ad relevance and information quality, drives perceived ad value. These core perceptions collectively inform behavioural intentions, specifically purchase intent and click willingness. This framework visually captures the cognitive, affective, and ethical dimensions underpinning technology acceptance, situating consumer attitudes and actions within a robust theoretical context that has been widely validated in technology adoption research(Carlos Martins Rodrigues Pinho & Soares, 2011; F. Davis, 1987; Koufaris, 2002; Lu et al., 2003; Venkatesh & Bala, 2008; Venkatesh & Davis, 2000).

Figure:1 Proposed Conceptual Model *"Factors Influencing Consumer Attitudes Toward AI-Enabled Advertising"*



Source: Authors' Compilation

8. Research Implications & Suggestions

The outcomes of this study provide critical managerial insights for advertisers, marketers, and platform developers who want to apply consumer-centric AI-enabled advertising strategies. The identification of *nine* distinct factors sheds light on the underlying psychological and behavioural mechanisms driving consumers perception regarding AI-generated advertisements in the Indian context. The constructs range from perceived privacy concerns to value perception and behavioural outcomes such as purchase intent and click Willingness. Each of these has actionable implications that can inform the design, deployment, and regulation of AI-driven marketing efforts.

8.1 Addressing Privacy Concerns

One of the most striking findings is the presence of *Perceived Privacy Intrusion* and *Perceived Privacy Assurance* as distinct but linked concepts. While the former reflects concerns about data misuse, the latter demonstrates customer trust in data protection procedures. Advertisers must go beyond compliance to implement proactive transparency strategies, such as real-time data usage notifications, opt-in consent systems, and streamlined privacy dashboards. These measures can assist to translate privacy concerns into trust, resulting in more positive customer responses to AI-based targeting.

8.2 Enhancing Personalization without Compromising Comfort

The survey found that consumers placed a high value on *Ad-Relevance*, indicating a preference for content suited to their interests and preferences. Over-personalization, on the other hand, may raise concerns about surveillance. Thus, marketers must prioritise contextual targeting over intrusive behavioural profiling. Personalisation tactics should be based on declared data (user choices) rather than inferred behavioural data alone to strike a balance between relevance and perceived intrusiveness.

8.3 Strengthening Consumer Trust

Trust was recognised as a key factor in shaping customer perceptions of AI-enabled advertisements. Firms must follow ethical AI norms, which include declaring the involvement of AI in ad generation or targeting and properly communicating the origins and accuracy of recommendations. Third-party audits and certifications of AI systems, as well as the incorporation of trust indicators (such as security badges or certified advertiser tags), can enhance the perception of legitimacy.

8.4 Designing Value-Centric Experiences

The study emphasises the dual character of *Ad-Value*, which includes both *utilitarian* and *hedonic* components. Marketers should concentrate on generating ad content that informs, entertains, and emotionally engages the audience. Using storytelling, interactivity, gamification, or immersive formats like augmented reality can improve the *perceived value* of AI-generated commercials and increase brand affinity.

8.5 Enhancing Perceived Information Quality

Customers expect AI-generated commercials to be *informative*, *relevant*, and *simple* to understand without being domineering. The aspect of *Perceived Information Quality* emphasises the importance of advertisements providing clear, actionable, and quality content that helps people make decisions. Excessively complicated or exaggerated communications might diminish efficacy and raise cognitive load over consumers’ mind. To improve perceived information quality, advertisers should prioritise clarity, practical benefits, and brand differentiation(Davies, 2001). AI technologies can help by using intelligent summarisation tools, natural language generation, and personalisation algorithms to customise the depth of data according to the user's preferences or behavioural patterns. The goal should be to deliver just enough information to inform users but not overwhelming them, hence increasing ad trust and enjoyment.

8.6 Addressing Information Disclosure Discomfort

The analysis revealed the persistence of *Information Disclosure Discomfort* as a unique component, indicating emotional resistance to perceived intrusiveness and overexposure in AI-enabled advertising(Milne et al., 2004; Phelps et al., 2000). Consumers' concerns about the scope of personal data usage, perceived surveillance, and a lack of openness in data handling processes frequently contribute to this uneasiness. To address these issues, marketers could implement techniques that encourage openness and increase consumer autonomy(Baek et al., 2014). Techniques including frequency capping, relevant ad placements, and user-control features (e.g., "hide this ad" or "why am I seeing this?" options) can empower users while reducing perceived coercion(Aguirre et al., 2015).

8.7 Encouraging Conversions through Trust and Utility

Purchase Intent and *Click Willingness* are direct indications of campaign efficacy. Ads must carefully guide customers through the buying funnel, using AI not only to capture their attention, but also to present appealing offers, clear calls-to-action, and seamless transitions to landing sites or in-app payment processes. Trust-enabling and relevance personalisation are critical enablers of these subsequent behaviours (Huh et al., 2020; Sirdeshmukh et al., 2002).

It is critical to recognise that some of these elements are both independent and interconnected. For example, *Perceived Trustworthiness* increases both *Purchase Intent* and *Click Willingness*, while *Perceived Ad-Relevance* improves both *Perceived Ad-Value* and *Perceived Privacy Assurance*. As a result, an integrative strategy that targets numerous dimensions at the same time, such as ethical AI, user-centric design, and transparent data practices, can result exponential engagement and hence conversions.

9. Limitations and Future Research Directions

9.1 Limitations

While this study provides useful insights into consumer imprints of AI-enabled advertising in India, it must be noted that there are significant limitations. First, the study is geographically and culturally specific, focussing primarily on Indian consumers.

Cultural differences in views towards privacy, trust, and technology use may restrict the findings' generalisability to Western or other Asian cultures, needing appropriate contextualisation. Second, the study used a cross-sectional approach to gather perceptions at a specific point in time. Longitudinal research may provide more dynamic insights as consumer views shift due to technical breakthroughs or strict legislative developments, such as the implementation of stronger data protection regulations. Third, relying on self-reported data has innate drawbacks, including the possibility of social desirability bias, recall problems, and misinterpretation of survey items. While reliability measures were generally acceptable, including behavioural data or observational approaches may improve the robustness of future findings. Finally, certain categories, particularly Click Willingness and Perceived Information Disclosure Discomfort, have lower Cronbach's alpha values, indicating possible weaknesses in measurement design. These constructs could benefit from additional refinement through qualitative research, expert validation, or scale construction to increase their clarity and comprehensiveness.

9.2 Future Research Directions

Future research can expand on the findings of this study in a variety of crucial directions. First, cross-cultural comparative research is required to understand how cultural norms, values, and legal frameworks influence consumer impressions of AI-enabled advertising. Such efforts would broaden the global applicability of theoretical models and inform more culturally sensitive marketing techniques. Second, longitudinal and experimental research methodologies can provide useful information about the changing nature of customer sentiments. Tracking changes over time or modifying specific ad attributes—such as transparency cues, personalisation depth, or data-use disclosures—may uncover causal correlations and increase our understanding of how consumers respond to emerging AI capabilities. Third, including behavioural and neuromarketing data—such as click-through rates, purchase behaviour, eye-tracking, or electroencephalography responses—can improve existing models by confirming self-reported notions like *Information Disclosure Discomfort* or *Perceived Ad-Value* with objective, real-time measurements. Fourth, future research should try to convert the current exploratory framework into a verified conceptual model through structural equation modelling (SEM). This would allow for the testing of mediating and moderating effects amongst components, resulting in a more sophisticated and predictive understanding of consumer behaviour in AI advertising ecosystems. Finally, considering the importance of characteristics such as *Perceived Privacy Intrusion* and *Trustworthiness*, more research into how customers view the ethical features of AI in advertising is required. Studies that look at the impact of data openness, opt-in methods, and computational comprehensibility on trust and regulatory compliance intents are especially promising in this era of increased online accountability.

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