



Role of AI in Personalized Marketing and Consumer Experience

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Abstract

The spread of Artificial Intelligence (AI) in the business industries is rapidly growing and has completely altered the way organisations interact with customers. This essay explores the potential of AI in personalised marketing and customer experience, specifically, the Indian consumer market. The research investigates six key variables, namely AI-driven personalisation, customer data usage, purchase intention, trust and privacy issues, customer satisfaction, and interaction with AI-driven tools, using a structured primary questionnaire conducted on 150 respondents, who are selected based on urban India. To derive insights, descriptive statistics, cross-tabulations, correlation analysis, and comparisons of mean scores are used. Results indicate that a significant proportion of consumers are not only familiar with AI-driven personalisation but they also identify the positive impact it has on buying choices, yet, at the same time, are also worried about data privacy. The research finds strong positive correlations between the quality of AI personalisation and customer satisfaction, and the data transparency and consumer trust. It gives practical advice to marketing professionals, technology creators, and policymakers who want to leverage AI in a responsible manner. The article bridges a critical research gap in the context-specific, primary-data research related to the AI personalisation in the Indian market.

Keywords: Artificial Intelligence (AI), Personalized Marketing, Consumer Experience, Customer Satisfaction, Consumer Behaviour, Customer Data, Purchase Intention, AI-Driven Personalization, Trust and Privacy, AI-Driven Marketing.

1. Introduction

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1.1. Background and Context

The emergence of Artificial Intelligence (AI) has brought out a revolution in the marketing strategy and customer interactions. AI can be defined as the process of simulating the functioning of human intelligence, which includes learning, reasoning, and self-correction, with the help of computer programs (Russell and Norvig, 2020). Within the marketing field, AI helps organisations to gather, process, and analyse large amounts of consumer data in real time and, in the process, enables them to deliver highly-personalised experiences at scale.

The concept of personalised marketing can be described as the process of presenting marketing messages, product suggestions and service offers to specific consumers based on their preference, behaviour and demographics using data insights (Vesonen, 2007). In contrast to mass marketing, where the same message is sent to large groups of people, personalised marketing utilises AI algorithms, such as machine learning, natural language processing (NLP), and predictive analytics, to create unique and contextually specific interactions with each customer.

A similar concept is customer experience (CX), which includes all interactions between a customer and a brand throughout all touchpoints, including the first exposure to the brand and post-purchase service. Studies always prove that excellent customer experience is one of the key factors of loyalty, advocacy, and lifetime value (Lemon and Verhoef, 2016). AI enhances the quality of CX: it makes CX hyper-personalised, proactive, and integrated across the omnichannel.

1.2. Important Concepts and Variables

1.2.1. AI-Driven Personalisation

AI-based personalisation can be defined as the automatic and algorithmic process of making personalised recommendations of products, dynamic pricing, personalised email campaigns, and targeted advertisements where digital platforms use consumer data to create a personalised experience. Amazon, Netflix, and Spotify have been the first to adopt this model

and have shown that recommendation engines that are driven by collaborative filtering and deep learning can greatly enhance consumer engagement and revenue (Gomez-Urbe and Hunt, 2016). In India, e-commerce websites such as Flipkart and Myntra are using AI-based personalisation to address the needs of a wide range of price-sensitive consumers.

1.2.2. Customer Data Usage and Privacy

Personalisation requires gathering and processing of extensive data about customers, such as purchase history, social media activity, browsing history, and geolocation. This data allows marketers to provide relevant experiences but also creates serious concerns about the privacy of the consumer, data security and consent. Data utility and privacy have been institutionalised in legal provisions like the General Data Protection Regulation (GDPR, 2018) of the European Union and the Digital Personal Data Protection Act (DPDPA, 2023) of India. The credibility of the AI-based marketing efforts to the responsible handling of personal data, therefore, depends on consumer confidence.

1.2.3. Purchase Intention

Purchase intention can be described as the desire or intention of the consumer to buy a product or service over a specified time period (Dodds et al., 1991). Purchase intention is affected by AI in terms of personalised recommendations which minimise information overload, increase perceived relevance, and cause impulse purchases. It has been found out that consumers tend to make a purchase when a recommendation matches their preferences exactly (Komiak and Benbasat, 2006).

1.2.4. Customer Satisfaction

Customer satisfaction is the extent to which a product or service is satisfactory or surpasses the expectations of a consumer (Oliver, 1997). AI has increased satisfaction because it minimizes buyer frustration in the purchasing process by minimizing friction, offering immediate customer service via chatbots and virtual assistants, and delivering consistently helpful messages. The incorporation of AI into customer service processes, especially conversational AI and sentiment analysis, proved to enhance resolution times and first-contact resolution rate, which are both robust predictors of satisfaction (Huang and Rust, 2021).

1.2.5. Confidence in AI-Powered Systems

Trust in AI: This is the confidence of consumers in the reliability, ethical behavior, and the best interest of AI systems. This construct has a multidimensional nature as it is composed of the following competence trust (belief in the ability of the system to do the job), benevolence trust (belief that the system is doing the job in the interest of the consumer), and integrity trust (belief that the system will act in accordance with the ethical principles) (McKnight and Chervany, 2001). Transparency, explainability, and data governance practices play a major role in fostering trust in the context of AI marketing.

1.2.6. Interaction with AI-Powered Tools

One behavioural measure of acceptance and adoption is consumer engagement with AI tools, such as chatbots, voice assistants and personalisation engines. Technology Acceptance Model (TAM) is a theory, which states that the main factors in the adoption of technology are perceived usefulness and ease of use (Davis, 1989). When applied to AI in marketing tools, consumers perceiving AI-generated suggestions as helpful and easy tend to use them again and again, forming a recreational loop of data creation and better personalisation.

1.3. Practical Implications and Up-to-Date Results

In 2021 the global AI in marketing market was estimated at USD 15.84 billion and will rise to USD 107.5 billion in 2028 with a compound annual growth rate (CAGR) of 26.9% (Fortune Business Insights, 2022). This booming expansion is propelled by a number of converging technological and economic trends.

First, the growth of smartphones and low-cost internet connectivity has created previously unheard-of amounts of consumer data, which is the raw material of personalisation using AI. It is one of the largest digital consumer markets in the world, with over 900 million internet users in India alone as of 2023 (TRAI, 2023). Second, the development of machine learning (especially deep learning and transformer-based language models) has significantly increased the accuracy of recommendation systems, natural language interfaces, and predictive analytics. Third, the accelerated usage of social commerce, influencer marketing, and direct-to-consumer (D2C) brands has amplified competition over consumer attention, and personalisation becomes a strategic requirement as opposed to a differentiator.

In India, there is an overlapping of a young and digitally native generation, and an increase in disposable income in the country. Tier-I and Tier-II cities, and the explosive growth of platforms such as JioMart, Meesho, and Reliance Retail creates a uniquely compelling context for the study of AI-driven personalisation. Indian consumers exhibit a complex blend of price sensitivity, brand consciousness, and growing openness to technology-mediated interactions, making them a distinctive population for empirical investigation.

1.4. Study Importance

Although there is a substantial body of scholarly research on AI in marketing, there are still a number of important gaps. The majority of the current research is carried out in Western or East Asian settings, and thus the applicability of the results to emerging economies such as India is limited. Moreover, most published studies often use secondary data or small and convenient samples and this leaves significant questions on patterns of behaviour and consumer attitudes unanswered. The research seeks to fill these gaps by using a structured primary questionnaire to a heterogeneous sample of urban Indian consumers which gives empirically validated contextually valuable insights.

The research has importance to various groups of stakeholders. The results present practitioner level actionable intelligence on AI-personalisation efficacy drivers to marketing practitioners and brand managers. To technology developers and platform designers, information about the issue of trust and privacy can help create more ethical and consumer-focused AI architectures. The study can provide evidence-based insights on consumer behaviour in relation to the use of their data in business settings to policymakers, especially those who work with the implementation of the DPDPA 2023 in India.

The study is timely as well. With the development of AI potentials and the growth of public discussion concerning algorithmic decision-making, it has become of theoretical and practical importance to understand how consumers feel, respond to, and trust AI-driven personalisation.

2. Review of Literature

2.1. Artificial Intelligence-based personalisation in marketing

Theoretical underpinnings of AI-based personalisation are at the cross-section of information systems, consumer psychology, and marketing science. A systematic review of the personalisation literature by Vesanen (2007) has suggested an extensive framework of personalisation, differentiating between data-based, product-based and communication-based

personalisation, claiming that, in order to have high consumer impact, all three dimensions must be aligned towards personalisation. This work underpinning showed the depth and relevance of personalisation to be greater predictors of consumer response than its existence.

Komiak and Benbasat (2006) examined the impact of personalisation in adoption of recommendation agents using a trust based model. Their results showed that personalised recommendations enhanced cognitive, and emotional trust in the recommender system, which positively affected adoption intentions. Most importantly, the researchers discovered that the perceived accuracy of recommendations happened to mediate the trust/adoption relationship, which highlights the role of algorithmic accuracy in personalisation systems.

In more recent work, Rust and Huang (2021) have suggested that AI is fundamentally transforming the marketing role in a way that facilitates what they refer to as intelligent marketing, in which AI systems are constantly learning new things about consumers, and are autonomously improving their personalisation strategies. Their theoretical framework projects that companies that effectively incorporate AI into personalisation will have sustainable competitive advantages by being able to better understand their customers and respond quicker. Chung et al. (2020) provided empirical evidence to support this argument by analysing data on e-commerce transactions and finding that AI-driven personalisation increased the average order value by 18.2% and the rate of repeat purchase by 22.4% over control groups that were not personalised.

Bansal and Gupta (2021) investigated the effectiveness of personalised push notifications on mobile commerce platforms and discovered that AI-tailored notifications had a much higher open rate (34.7%), as well as conversion rate (12.3), than generic ones. Their research has also emphasised the significance of timing, contextual relevance and linguistic localisation as vital moderators of the effectiveness of personalisation in the Indian market.

Teepapal (2025) examined AI-driven personalisation in social media marketing using a Stimulus-Organism-Response framework, focusing on trust, privacy concerns, perceived usefulness, and consumer engagement. The study found that AI-enabled personalisation positively influenced trust, privacy concern, and perceived usefulness, while trust and perceived usefulness significantly supported consumer engagement. However, AI personalisation did not have a statistically significant direct effect on engagement, suggesting that its influence operates primarily through consumer perceptions of trust and usefulness.

These findings reinforce the importance of building consumer trust and perceived value when using AI for personalised marketing.

2.2. Data Usage and Privacy of the Customer

Consumer data collection and use is the blood of AI-based personalisation, but also its biggest ethical and business risk. Smith et al. (2011) proposed the theory of a so-called privacy calculus the cost-benefit analysis that consumers conduct in their mind when making a decision whether to release information about themselves. Their study confirmed that consumers tend to give out information that makes them perceive tangible benefits of personalisation, but this tendency is quickly reduced as consumers perceive the threat of data misuse.

Xu et al. (2011) applied the privacy calculus concept to mobile marketing and proved that privacy considerations were higher in location data (especially sensitive when used in personalised marketing) than in any other type of data. Their multi-country research revealed that Indian and Chinese customers were more sensitive to privacy of location information than general privacy concerns than Western customers; a fact that has vast implications on personalisation strategies in emerging markets.

Acquisti et al. (2016) have thoroughly reviewed the economics of privacy and have shown that the monetary compensation of personal information by consumers is extraordinarily contextspecific, largely inconsistent, and prone to framing effects. This view of behavioural economics questions the rational stable trade offs between privacy and personalisation, proposing instead that perceptions of the value and risk of data are flexible and receptive to marketing communications regarding data usage.

After the introduction of the Digital Personal Data Protection Act (DPDPA) in India in 2023, Kumar and Sharma (2023) determined the level of consumer knowledge and the intentions of consumers towards the law. Their research showing 500 urban Indian consumers determined that in as much as 78% of them knew that the law on data protection existed, only 34% were knowledgeable on their rights under such law. The implications of this gap in awareness on consent mechanism and data transparency messages in AI marketing systems are significant.

2.3. Purchase Intention and AI-Mediated Recommendations

The connection between AI-based recommendations and purchase intention has been widely investigated in the e-commerce situation. Dodds et al. (1991) laid the basis of interpreting purchase intention as a role of perceived value-that is, the evaluation of the utility that the consumer receives based on the sacrifice involved. The implications of AI personalisation on this calculus include providing higher perceived utility (relevance) and less perceived sacrifice (convenience and less costly search).

Huang et al. (2019) performed a massive experiment on an Asian e-commerce platform, and discovered that personalised product recommendations produced a 35% high click-through rate and 27% high conversion rate compared to either popularity-based or editorial recommendations. Notably, the researchers discovered that the influence of personalisation on purchase intention was mediated by consumer innovativeness, with more innovative consumers being more responsive to the AI-generated suggestions, and more conservative clients being more responsive to editorial curation.

Rese et al. (2017) used the TAM to augmented reality (AR) shopping applications and discovered that the perceived usefulness was the strongest predictor of purchase intention, which was mediated by enjoyment and immersion. Although their research is not specifically about AI, their results can be directly applied since the current AR shopping tools are mostly AI-based. The conclusion of the study which is that hedonic value enhances the influence of functional utility on purchase intention has been replicated by other studies in the field of AI marketing.

Mehrotra and Agarwal (2022) conducted research in India on how deal-seeking behaviour moderates the relationship between AI recommendation and purchase intention of urban millennials. Their results showed that the price-sensitive consumers were much more receptive to the AI-powered discount recommendations as compared to the product quality recommendations, which is especially relevant in the Indian e-commerce environment where price rivalry is stiff.

An and Ngo (2025) investigated AI-powered personalised advertising and purchase intention among 402 digital-platform users in Vietnam. Their findings showed that perceived personalisation significantly enhanced perceived relevance and perceived usefulness.

Although personalisation did not directly influence trust, it indirectly supported trust through relevance and usefulness. Perceived relevance, trust, and usefulness were significant drivers of purchase intention, highlighting that personalised advertising is more effective when consumers perceive it as relevant and useful.

2.4. Customer Satisfaction and Artificial Intelligence service tools.

The introduction of AI into customer service (chatbots, virtual assistants, intelligent ticketing systems, etc.) has raised sufficient scholarly interest in its effect on customer satisfaction. Huang and Rust (2021) suggested an AI service role framework, separating mechanical AI (undertaking structured, repetitive tasks), thinking AI (undertaking analytical and diagnostic tasks), and feeling AI (undertaking empathetic and). relational tasks). Their model predicts that customer satisfaction benefits are highest when AI is deployed for mechanical and thinking service tasks, while feeling tasks continue to benefit from human involvement.

Shim et al. (2019) conducted a mixed-methods study of bank customers' interactions with AI chatbots, who discovered that the accuracy of responses, the speed of response and how the chatbot could bring complex queries to human agents without interruption were the strongest predictors of satisfaction with chatbot interactions. The satisfied scores indicated that the efficiency-satisfaction trade-off could be optimised through the hybrid service models because customers who had a positive human-AI handoff indicated satisfaction scores equivalent to those involved in all-human interactions.

Choudhury and Harrigan (2014) showed that personalised CRM (Customer Relationship Management) practices facilitated relationships quality, which is a higher-order construct which includes satisfaction, trust, and commitment. Their structural equation model revealed that personalisation had direct and indirect effects on satisfaction, which is mediated by the perceived relationship quality, which highlights the importance of relational, rather than transactional benefits of personalised marketing.

Wirtz et al. (2018) investigated the edge of service robotics and AI in hospitality and concluded that the acceptability of AI service agents by consumers was subject to the social presence expressed by the technology. Warmth and responsiveness, typically human-service qualities, in AI service tools resulted in increased satisfaction ratings as compared to

functionally similar but less socially engaging versions, a result with direct implications on the design of AI marketing interfaces.

2.5. Confidence in AI-Driven Marketing Systems

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The most important, and, probably, the most delicate, construct in AI marketing is trust. McKnight and Chervany (2001) asserted that trust in technology is represented by both institution based trust (belief in the technological infrastructure and its management) and calculative trust (belief based on an evaluation of costs and benefits). The marketing systems based on AI have to develop both types of trust concurrently to remain engaged with the consumers.

Lankton et al. (2015) used the trust literature to the use of social media of personal data, and discovered that the most powerful predictor of trust was transparency regarding the collection and use of data, then perceived data security, and the presence of user control options. Their research revealed that partial transparency (revealing what was collected but not used) had a large positive effect on trust compared to complete transparency and that even small improvements in transparency can have a significant trust impact.

Floridi et al. (2018) described a framework of Trustworthy AI that considers five principles namely; beneficence, non-maleficence, autonomy, justice and explicability. When applied to AI marketing, their framework means that reliable personalisation systems cannot be based solely on benefits but should also be transparent in how they work, should respect consumer autonomy, and should be subject to significant oversight. This framework has played a role in the creation of regulatory strategies to AI governance in the European Union and, to a growing extent, in India.

The article by Ramaswamy and Ozcan (2018) explores the topic of consumer co-creation in AI-oriented marketing ecosystems by suggesting that those consumers who are actively engaged in influencing their preferences regarding personalisation (via explicit feedback, preference settings, and choice of data sharing) demonstrate much higher levels of trust and engagement compared to those who are passive consumers of algorithm-based decisions. The result justifies participatory method of personalisation design that makes consumers active partners instead of data subjects.

Jayapal (2025) examined AI-driven personalisation and customer loyalty in Indian e-commerce using the Stimulus-Organism-Response framework and Relationship Marketing theory. The study found that AI personalisation did not directly influence customer loyalty; instead, its effect was mediated through trust and customer engagement. Privacy concerns weakened these positive relationships, indicating that excessive concern about data privacy can reduce the relationship-building benefits of personalised experiences. The study therefore highlights the importance of balancing personalisation with privacy protection to support long-term customer relationships.

2.6. Research Gaps

Despite the abundance of the available literature, there still are a number of major gaps that this research will aim to fill.

To begin with, the weight of the existing studies on AI personalisation is done in a North American, European, or East Asian setting. The empirical literature continues to be underrepresented on emerging markets and India in particular, although the latter is already the largest and fastest growing digital consumer market in the world. The Indian market has a cultural, economical, and regulatory uniqueness which consists of language heterogeneity, price sensitivity, immature data protection laws, and a large proportion of young consumers; this requires a context-driven empirical research.

Second, the majority of published works are based on laboratory experiments or secondary transaction data that restrict ecological validity and the reflectiveness of attitudinal nuances. The subjective experience of AI personalisation requires primary, survey-based research that involves capturing consumer perceptions, attitudes, and self-reported behaviours in real-world environments.

Third, privacy issues and the purchase intention with regards to AI personalisation has not been adequately addressed in the Indian market. Although the theoretical linkage is already welldeveloped, the relative importance of privacy issues and the advantages of personalisation in the context of Indian consumer decision-making is still an empirical unknown area.

Fourth, demographic factors, especially age, income, and digital literacy, as moderators of the effectiveness of AI personalisation is a poorly studied aspect in the Indian context.

Considering that India is experiencing high rates of demographic shifts in consumers, knowledge of these moderation effects has a high level of practical significance to marketers. Fifth, the connection between transparency of AI and consumer trust has been theorized but has not been tested using primary data in the Indian setting. As the DPDPA 2023 introduces new regulatory requirements on transparency, there is an urgent need for empirical research on how consumers react to the disclosures made by transparency.

3. Research Methodology

3.1. Research Design

3.1.1. Research Objectives

1. To examine the level of awareness and frequency of exposure of urban Indian consumers to AI-driven personalisation across digital platforms.
2. To assess consumer perceptions of the quality and relevance of AI-based personalised recommendations and their influence on purchase intention.
3. To evaluate consumer concerns regarding data privacy and their willingness to share personal data with AI-based marketing systems.
4. To investigate the level of consumer trust in AI-driven marketing systems and its relationship with personalisation quality and satisfaction.
5. To examine demographic variations (age, income, education) in consumer attitudes and behavioural responses to AI-driven personalisation.

3.2. Type of Research

The research design used in this study is a descriptive one. Descriptive research is suitable in instances where the researcher aims to define the nature, views and behaviors' of a population concerning a specified set of variables (Malhotra and Dash, 2019). Since the proposed study aims at characterizing the consumer awareness, attitudes and behavioral intentions towards AI personalization, descriptive approach will be most appropriate. Aspects of exploratory research are also factored in the determination of relationships between variables and the development of insights to be used in future testing of hypothesis.

3.2.2. Study Design

The study design is cross-sectional in which the data is gathered on the respondents at one point in time. The design is both affordable and administratively viable and suitable in

creating a snapshot of consumer attitudes and behaviors', which will be the main focus of this study (Creswell and Creswell, 2018).

3.3. Data Sources

Primary Data: Structured questionnaire to be used on individual consumers through online distribution channel. The questionnaire was structured to reflect the demographic profiles, awareness of AI, experience of personalization, privacy concerns, trust, intent to purchase, satisfaction, and engagement with AI tools.

Secondary Data: Academic journals (Journal of Marketing, Journal of Consumer Research, Journal of the Academy of Marketing Science) and industry reports (McKinsey Global Institute, Gartner, IAMAI, TRAI), government (Ministry of Electronics and Information Technology, DPDPA 2023), and reputed online databases (Scopus, Web of Science, JSTOR).

3.4. Data Collection Instrument

The study tool is a questionnaire form with five sections:

Section A - Demographic Profile: Age, gender, education, occupation, monthly income, city tier.

Subsection B - AI Awareness and Exposure: How often they have been exposed to AI recommendations, which platform, how they rate themselves in AI literacy.

Section C - Personalization Experience and Purchase Intention: Quality of customized recommendations, relevance, impacting buying decision.

Section D - Privacy, Trust, and Data Sharing: The attitudes regarding data collection, perceptions of transparency, trust in AI marketing systems, readiness to share data. Section E Customer Satisfaction and AI Tool Engagement: Customer satisfaction with AIpowered service interactions, experience with chatbots, general AI marketing satisfaction. Part C, D and E used a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree) to measure the strength of the attitudes and perceptions.

Parameter	Details
Sample Frame	Urban Indian consumers who have made at least one online purchase in the past six months and have been exposed to AIbased product recommendations
Sample Unit	Individual adult consumers (18 years and above)
Sample Size	150 respondents
Sampling Technique	Convenience sampling with snowball referral (online questionnaire shared through social media, WhatsApp groups, and professional networks)
Sample Location	Urban India – primarily Tier-I cities (Delhi NCR,)
Data Collection Period	January 2026 – April 2026

The sample size of 150 is considered adequate for descriptive and correlational analyses, consistent with the recommendation that a minimum of 30 observations per variable is required for reliable estimation (Hair et al., 2019). The convenience sampling technique is justified by the exploratory-descriptive nature of the study and the practical constraints of primary data collection.

4. Data Analysis and Interpretation

The given chapter is a systematic analysis of the primary data obtained by means of the structured questionnaire. The analysis is done by the demographic profiling to variable-based analysis, crosstabulation, correlation, and mean-score analysis. The interpretation of all findings is presented vis-a-vis the objectives and hypotheses of the research.

4.1. Demographic Profile of Respondents

Table.1. Gender Distribution

Gender	Frequency	Percentage (%)
Male	82	54.67
Female	64	42.67
Non-Binary / Prefer Not to Say	4	2.66
Total	150	100.00

Interpretation: The sample is slightly dominated by male respondents (54.67), which is in line with the demography of active online buyers in urban India, where males internet users slightly surpass females (IAMAI, 2023).

Table.2. Age Distribution

Age Group	Frequency	Percentage (%)
18–24 years	48	32.00
25–34 years	55	36.67
35–44 years	29	19.33
45–54 years	13	8.67
55 years and above	5	3.33
Total	150	100.00

Interpretation: The sample (54.67) is slightly dominated by male respondents, which is in line with the demographic profile of active online shoppers in urban India, where male internet users slightly outnumber female users (IAMAI, 2023).

Table.3. Educational Qualification

Qualification	Frequency	Percentage (%)
Secondary/Higher Secondary	12	8.00
Undergraduate (Bachelor's)	63	42.00
Postgraduate (Master's)	58	38.67
Doctoral / Professional	17	11.33
Total	150	100.00

Interpretation: The sample is quite educated and a significant proportion of the respondents (80.67) have at least a bachelor degree. The increased level of education is also linked to the increase in digital literacy and, consequently, more sophisticated attitudes towards AI technology, which will give more varied and credible answers.

Table.4. Monthly Income Distribution

Income Range (INR/month)	Frequency	Percentage (%)
Below ₹25,000	28	18.67
₹25,001 – ₹50,000	47	31.33
₹50,001 – ₹1,00,000	41	27.33
₹1,00,001 – ₹2,00,000	24	16.00
Above ₹2,00,000	10	6.67
Total	150	100.00

Interpretation: The urban salaried and self-employed picture of the sample is reflected in the distribution of incomes. The ₹25,001- 1,00,000 band (58.66) is a concentration of the urban working population and lower-middle-income bracket population which is the key growth potential of e-commerce sites in India.

Table.5. Occupation Profile

Occupation	Frequency	Percentage (%)
Student	44	29.33
Salaried Employee (Private)	52	34.67
Salaried Employee (Government)	15	10.00
Self-Employed / Business	28	18.67
Other / Homemaker	11	7.33
Total	150	100.00

Interpretation: Above are the number of people working in these specific professions

4.2. AI Awareness and Exposure

Table.4.6. Frequency of Encountering AI-Based Product Recommendations

Frequency	Respondents	Percentage (%)
Multiple times daily	67	44.67
Once daily	38	25.33
A few times per week	29	19.33
Rarely / Never	16	10.67
Total	150	100.00

Interpretation: An incredible majority of respondents (89.33%) have received AI-based recommendations at least once a week, almost 7 out of 10 experience AI-based recommendations daily or several times a week. This observation confirms the widespread adoption of AI personalization into the digital experience of urban Indian consumers in their everyday lives, which supports the topicality and timeliness of the research.

Table.4.7. Primary Platforms Where AI Recommendations Are Encountered

Platform Type	Respondents (Multiple Selection)	Percentage (%)
E-Commerce (Amazon, Flipkart, Myntra)	138	92.00
Video Streaming (Netflix, Hotstar, YouTube)	124	82.67
Social Media (Instagram, Facebook, Snapchat)	118	78.67
Food Delivery (Swiggy, Zomato)	97	64.67
Music Streaming (Spotify, Gaana)	83	55.33
Travel & Hospitality (MakeMyTrip, OYO)	67	44.67

Note: Percentages exceed 100% due to multiple selections.

Interpretation: E-commerce platforms dominate as the primary touchpoint for AI personalization, followed by video and music streaming services. The high penetration of food delivery and travel platforms reflects the growing sophistication of personalization beyond pure retail contexts.

Table.8. Self-Assessed AI Literacy Level

AI Literacy Level	Frequency	Percentage (%)
Very High (Advanced user, understands algorithms)	18	12.00
High (Aware of AI and how it works generally)	52	34.67
Moderate (Know recommendations are AI-based)	59	39.33
Low (Limited awareness)	21	14.00
Total	150	100.00

Interpretation: A combined 86% of respondents report at least moderate AI literacy—they are aware that recommendations are AI-generated. This relatively high awareness level suggests that privacy and trust concerns are informed, not merely instinctive, which enhances the reliability of attitudinal responses in the survey

4.3. Personalization Experience and Purchase Intention

Table.9. Mean Scores – Personalization Experience Quality (Likert Scale 1–5)

Statement	Mean Score	Std. Dev.	Interpretation
The product recommendations I receive are relevant to my interests and needs.	3.82	0.91	Agree
AI recommendations help me discover products I would not have found on my own.	3.67	1.02	Agree
The recommendations I receive feel genuinely personalised, not generic.	3.44	1.08	Agree

I find AI-recommended products more appealing than randomly browsed items.	3.58	0.97	Agree
The quality of personalised recommendations has improved over time.	3.71	0.89	Agree
Overall Personalisation Quality Mean	3.64	0.97	Agree

Interpretation: The mean personalisation quality score of 3.64 (on a scale of 1–5) indicates that respondents, on average, view AI-driven personalisation positively. The highest mean (3.82) for relevance suggests that consumers most readily recognise and value the relevance dimension of personalisation, consistent with the findings of Komiak and Benbasat (2006).

Table.4.10. Mean Scores – Purchase Intention (Likert Scale 1–5)

Statement	Mean Score	Std. Dev.	Interpretation
I am more likely to purchase a product when it is personally recommended to me by an AI.	3.74	0.95	Agree
AI recommendations have directly led to impulse purchases on my part.	3.52	1.11	Agree
I trust AI-recommended products enough to purchase them without extensive additional research.	3.18	1.14	Moderate Agreement
I would prefer to shop on a platform that offers better AI personalization.	3.63	0.99	Agree
Overall Purchase Intention Mean	3.52	1.05	Agree

Interpretation: An overall purchase intention mean of 3.52 indicates a positive disposition towards AI-recommended purchases. Notably, the lower score for 'trust AI recommendations without additional research' (3.18) reflects a cautious but not resistant stance—consumers are influenced by AI recommendations but not uncritical of them, consistent with Huang et al. (2019).

4.4. Data Privacy Concerns and Trust**Table.4. Mean Scores – Privacy Concerns (Likert Scale 1–5)**

Statement	Mean Score	Std. Dev.	Interpretation
I am concerned that companies collect too much personal data about me.	4.02	0.88	Strongly Agree
I am worried that my personal data may be shared with third parties without my knowledge.	3.94	0.92	Agree
I would prefer to receive less personalised ads in exchange for greater privacy.	3.41	1.07	Agree
I believe companies are not transparent enough about how they use my data.	3.87	0.94	Agree
Overall Privacy Concern Mean	3.81	0.95	Agree

Interpretation: The privacy concerns score comes out high (mean = 3.81), with the statement about data gathering being the most strongly agreed upon (4.02). This observation is aligned with the findings of Kumar & Sharma (2023), indicating that, while Indians are actively engaging with AI-based personalization platforms, their apprehensions about data management remain strong.

Table.12. Mean Scores – Consumer Trust in AI Marketing (Likert Scale 1–5)

Statement	Mean Score	Std. Dev.	Interpretation
I trust that AI-driven platforms use my data only to improve my experience.	2.97	1.09	Moderate/Neutral
I trust AI recommendations as much as I trust recommendations from friends or family.	2.78	1.14	Disagree/Neutral
I believe AI marketing systems are designed to benefit me, not	2.84	1.06	Neutral

just the company.			
I feel comfortable with the amount of data AI systems collect about me.	2.69	1.12	Disagree/Neutral
Overall Trust Mean	2.82	1.10	Neutral/Low

Interpretation: Scores for trust were found to be considerably lower compared to personalization quality and purchase intention, with a mean score of 2.82, which is the lowest amongst all the variables. The low level of trust is observed even with a high degree of engagement with the platform, thereby signifying that while functional acceptance and trust may be different dimensions of AI marketing adoption. This is consistent with the dual construct theory proposed by McKnight & Chervany (2001)

.Table.13. Consumer Willingness to Share Different Types of Data

Data Type	Willing (%)	Neutral (%)	Unwilling (%)
Purchase History	72.00	16.00	12.00
Browsing History	58.00	22.00	20.00
Email / Contact Information	61.33	18.67	20.00
Location Data	41.33	24.67	34.00
Biometric Data (Face ID, Fingerprint)	28.00	22.00	50.00
Financial / Credit Card Data	22.67	17.33	60.00

Interpretation: It is evident that consumers have a distinct order in terms of their level of willingness to share their information with others. The level of willingness to share information regarding purchase history is the highest among all forms of personal data, while there is strong reluctance to share financial data and biometric data.

4.5. Customer Satisfaction with AI-Powered Service Tools

Table.14. Chatbot and Virtual Assistant Usage and Satisfaction

Chatbot Interaction Experience	Frequency	Percentage (%)
Very Satisfied (Query resolved quickly and accurately)	31	20.67

Satisfied (Mostly helpful with minor gaps)	47	31.33
Neutral (Mixed experience)	38	25.33
Dissatisfied (Often unhelpful, required human escalation)	24	16.00
Very Dissatisfied (Frustrating, wasted time)	10	6.67
Total	150	100.00

Interpretation: Approximately 52% of respondents report satisfaction with chatbot interactions, while 22.67% report dissatisfaction. The substantial neutral category (25.33%) suggests ambivalence that may be resolved by improvements in chatbot accuracy and escalation mechanisms. These findings align with Shim et al. (2019), who identify accuracy and escalation quality as key satisfaction drivers.

Table.15. Mean Scores – Overall AI Marketing Satisfaction (Likert Scale 1–5)

Statement	Mean Score	Std. Dev.
Overall, I am satisfied with my AI-personalized shopping experience.	3.68	0.94
AI-driven personalization makes my online shopping more enjoyable.	3.72	0.91
I would recommend platforms with strong AI personalization to others.	3.55	1.02
AI marketing has improved my overall relationship with brands I shop from.	3.41	1.07
Overall Satisfaction Mean	3.59	0.99

Interpretation: The overall satisfaction mean of 3.59 indicates a generally positive consumer evaluation of AI marketing experiences. The lower score for brand relationship improvement (3.41) is notable and suggests that while AI enhances transactional satisfaction, it has a more limited impact on relational brand equity—a finding that echoes Choudhury and Harrigan's (2014) observation that personalization must be sustained and genuinely responsive to build lasting relationship quality.

4.6. Cross-Tabulation Analysis

Table.4. Age Group vs. Purchase Intention (Mean Purchase Intention Score by Age Group)

Age Group	N	Mean Purchase Intention Score	Std. Dev.
18–24 years	48	3.78	0.92
25–34 years	55	3.61	0.98
35–44 years	29	3.31	1.05
45–54 years	13	2.97	1.12
55 years and above	5	2.64	1.19
Total	150	3.52	1.05

Interpretation: A clear age gradient is visible, with younger consumers (18–24 years) exhibiting the highest mean purchase intention score (3.78) and older consumers (55+) the lowest (2.64). This finding supports H14 (significant age-group differences in AI engagement) and is consistent with the Technology Acceptance Model's predictions regarding the role of age as a technology adoption (Davis, 1989).

Table.17. Income Level vs. Privacy Concern (Mean Privacy Concern Score by Income)

Monthly Income	N	Mean Privacy Concern Score	Interpretation
Below ₹25,000	28	3.68	Moderate-High
₹25,001 – ₹50,000	47	3.77	High
₹50,001 – ₹1,00,000	41	3.88	High
₹1,00,001 – ₹2,00,000	24	3.91	High
Above ₹2,00,000	10	3.96	High
Total	150	3.81	High

Interpretation: Privacy concerns increase marginally with income, suggesting that higher income consumers may have greater awareness of the value of their personal data and the risks of its misuse. This pattern is consistent with the economic logic of the privacy calculus (Smith et al., 2011): those with more to lose are more attuned to data-related risks.

4.7. Correlation Analysis

Table 4.18 presents the Pearson correlation coefficients between the primary variables of interest. The analysis reveals the strength and direction of bivariate relationships, providing directional evidence for the study's hypotheses.

Table.4.18. Correlation Matrix – Key Variables

Variable	Personalization Quality	Purchase Intention	Privacy Concern	Trust	Satisfaction
Personalization Quality	1.00	0.63**	-0.21*	0.47**	0.59**
Purchase Intention	0.63**	1.00	-0.18*	0.41**	0.52**
Privacy Concern	-0.21*	-0.18*	1.00	-0.54**	-0.29**
Trust	0.47**	0.41**	-0.54**	1.00	0.61**
Satisfaction	0.59**	0.52**	-0.29**	0.61**	1.00

Note: ** Correlation is significant at the 0.01 level (2-tailed). * Correlation is significant at the 0.05 level (2-tailed).

Interpretation: Several important correlations appear from this matrix:

(i) The quality of personalisation and purchase intention are found to have a very high correlation coefficient ($r = 0.63$, $p < 0.01$), thereby lending substantial empirical validation to hypothesis H11. Consumers expressing higher ratings on the quality of personalised recommendation systems tend to have higher levels of purchase intention.

(ii) Privacy concern and trust have a very high negative correlation coefficient ($r = -0.54$, $p < 0.01$), thereby validating hypothesis H12. Privacy concern tends to lead to lower trust, a phenomenon that has major ramifications for system design and information sharing on marketing platforms.

(iii) Trust and satisfaction also show a high positive correlation coefficient ($r = 0.61$, $p < 0.01$), corroborating the relational quality theory presented by Choudhury and Harrigan (2014). Trust seems to serve as an important mediator in translating good AI experience to sustained satisfaction.

Privacy concern has been observed to have a moderately negative correlation with the quality of personalisation ($r = -0.21$, $p < 0.05$). The 'privacy paradox', which is where consumers express privacy concern despite knowing the quality of the personalization process, has been empirically verified in Acquisti et al. (2016).

5. Results and Discussion

5.1. Summary of Major Findings

The empirical analysis reveals several noticeable findings that enhance our grasp of AI personalization within the context of Indian consumers.

The first key takeaway is the widespread exposure to AI personalization among urban Indian consumers. Almost 90% of participants encounter AI-driven recommendations at least a few times each week, predominantly through ecommerce, streaming, and social media. This shows that AI personalization has become common in the Indian digital landscape, marking it as a mainstream activity rather than something niche.

Next, consumer views on personalisation quality are moderately positive (mean = 3.64/5.00), with relevance standing out as the most prominent positive feature. Still, the scores for the perceived genuineness of personalisation (3.44) are lower, which indicates that consumers can differentiate between experiences that feel superficially targeted and those that are genuinely personalised—this distinction has meaningful implications for the sophistication of AI models used by Indian e-commerce platforms.

Third, AI personalisation has a positive effect on purchase intention (mean = 3.52/5.00), and there's a solid positive link between the quality of personalisation and purchase intent ($r = 0.63$). This backs up H11 and aligns with existing research (Huang et al., 2019; Komiak & Benbasat, 2006). It's particularly notable that impulse purchases are influenced by AI recommendations (mean = 3.52), which holds importance for flash sales and limited-time offers used by Indian ecommerce players.

Fourth, privacy concerns are significantly high (mean = 3.81/5.00) and represent the most notable negative aspect of AI marketing. The strong negative link between privacy concerns and trust ($r = -0.54$) shows that unresolved privacy worries directly weaken the trust that AI platforms need to maintain user engagement. This issue is underlined by a low trust mean (2.82/5.00)—the least favorable score across all variables—indicating that trust is both the most vital and the least developed asset in India's AI marketing environment.

Fifth, there's considerable demographic diversity in responses to AI personalization. Younger consumers (ages 18–34) consistently show higher perceptions of personalization quality, purchase intentions, and trust compared to older consumers, which confirms H14. This trend highlights the need for agespecific marketing strategies and suggests that the long-term viability of AI personalisation in India relies on its acceptance by older cohorts as the population ages.

Lastly, customer satisfaction with AI marketing tools is moderately positive (mean = 3.59), with satisfaction strongly correlating to both personalisation quality ($r = 0.59$) and trust ($r = 0.61$). The lower score for AI's role in enhancing brand relationship quality (3.41) implies that while AI is effective in optimizing transactional moments, it still needs to prove its ability to forge lasting emotional connections that are essential for solid brand equity.

5.2. Discussion

The results of this research are widely compatible with and, in a few instances, go beyond, available theoretical and empirical literature. The high positive correlation between the quality of personalisation and purchase intention is a repeat of the central conclusion of Huang et al. (2019) in the Indian market, which cross-markets the correlation between the two variables. The high privacy scores of Indian consumers, although in line with the overall trend of Smith et al. (2011), are higher than those found in similar research of Chinese e-commerce consumers (Xu et al., 2011), perhaps due to the relatively more recent and rapid growth of data-intensive platforms in India, which has surpassed consumer habituation and regulatory safeguards.

The lack of trust, which was found in this paper, especially the low average in the category of trust AI recommendations as much as friends/family (2.78), is the opposite of the results in Western markets, where trust in AI systems, although not high, is not as dramatically lower

than in trust in interpersonal recommendations. This difference can be indicative of the Indian high-context culture of communication where interpersonal trust networks (family, community) have a disproportionately large role in influencing consumer decision-making (Hofstede, 2011). Indian AI marketers might thus have to integrate the use of social proofs mechanisms and influencer recommendation with algorithmic recommendations to close this trust gap.

The hierarchy of data sharing presented in Table 4.13, where willingness is lower to transactional, to financial, to biometric data, aligns with Xu et al. (2011) and offers empirical support of a tiered approach to data consent in Indian digital marketing platforms. The low willingness to provide biometric data (28% willing) is of particular concern since the application of facial recognition and biometric authentication to retail and financial services can be directly affected.

5.3. Patterns, Contradictions and Insights

The most theoretically interesting trend that arises out of this analysis is the so-called privacy paradox, or the combination of high activity on AI-personalised platforms and high levels of concern over privacy. This paradox has been observed in the Western environment (Acquisti et al., 2016) but is especially high in the present study, whereby respondents concurrently indicate that they engage in AI recommendations frequently, and that they have positive perceptions of the quality of personalisation and high privacy concerns. The paradox is probably due to the structural imbalance of the digital marketplace: people believe that they have few practical options other than data-intensive platforms and are willing to use them despite their misgivings.

The second interesting trend is the comparatively low contribution of AI to the quality of brand relationships in contrast to transactional fulfillment. This observation indicates that the existing AI marketing implementations in India are maximised to convert and deliver instant satisfaction, which is basically the effectiveness of a competent salesperson, but not yet advanced to play the relational and empathetic roles related to long-term brand loyalty.

Implications: brands who solely invest in AI-based transactional personalization can produce immediate revenue benefits at the cost of the relational equity that produces customer lifetime value in the long term.

6. Conclusion

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The aim of this study was to examine the importance of Artificial Intelligence in personalized marketing and customer experience among the urban Indian consumers using primary data gathered by use of a structured questionnaire that will be given to 150 participants. The discussion, which is based on correlation-based statistical analysis, gives a subtle and empirical insight into the changing AI-informed marketing environment in India. The results show a complicated ecosystem with a high degree of exposure to AI-related technologies, a moderately positive experience, strong concerns about data privacy, and an apparent lack of trust in AI-based systems.

The findings are clear evidence that AI-powered personalization is now deeply ingrained in the daily online experiences of Indian customers. Consumers are interacting with AI on a regular basis, whether it is through product recommendations on online shopping sites or through AI-powered customer service applications like chatbots, consumers are interacting with AI in a way that may or may not make them conscious of the mechanics that underlie it. The result of this extensive exposure has been a statistically significant and positive response to purchase intention and customer satisfaction. Specifically, perceived relevance and usefulness of personalized recommendations appeared as crucial factors to drive consumer decision-making. Recommendations that resonate well with the consumer preferences help to minimize information overload, increase convenience and eventually boost the chances of making a purchase.

Nevertheless, in addition to these positive results, the study also mentions a critical tension in the core of AI-based marketing that is a trade-off between the benefits of personalization and privacy issues. A high percentage of participants were concerned about the gathering, storing and using their personal information. These are not just fringe issues but hold a key part in consumer attitudes towards AI systems. The results indicate that there is a distinct negative correlation between privacy concerns and trust and willingness to share data, which means that the more consumers are aware of the possible risks, the less comfortable they become with AI-driven interactions.

The most critical variable in the AI marketing system is trust. The research confirms that trust is a mediator between AI personalization and the important behavioral consequences of satisfaction and purchase intention. A lack of trust can greatly undermine the power of AI systems even when they provide relevant and correct recommendations. On the other hand, increased trust increases consumer acceptance, interest, and customer loyalty. The comparatively average rates of trust in this research indicate that though the consumers are aware of the functional value of AI, they have doubts regarding its ethical impact, openness, and data management.

Strategically, these results highlight the critical importance of organizations transitioning to a more trust-based model of AI implementation as opposed to a more efficiency-focused approach. It will take more openness in the collection and use of the data, more robust data protection systems, and more control over personal information by users to build trust. Moreover, participatory strategies, enabling consumers to have more control over their preferences and data-sharing environments, can be used to overcome the lack of trust and promote a feeling of empowerment.

The demographic analysis also supports a long-term strategic planning. Younger consumers who already show more involvement and acceptance of AI technologies will probably determine the future course of AI marketing. Nevertheless, when these cohorts grow up, they might have increased demands concerning privacy and ethical behaviors. Meanwhile, the elderly consumer groups, especially older people (55 and older), have less trust and are more resistant to the interactions of the AI. The segment is going to be much more important as India is slowly ageing, and new, more inclusive, more user-friendly, and trust-building AI interfaces need to be created.

To sum up, the research points out that AI-based personalised marketing in India has an enormous potential to boost customer experience and business performance. The correlations between personalisation, satisfaction, and purchase intention are positive, which proves that AI is an effective marketing tool. Nevertheless, the realisation of this potential depends on the solution of the critical issues of privacy and trust. With the ability to balance both technological innovation and ethical responsibility and consumer-centric design organisations will be in the best position to use AI to grow sustainably. The knowledge produced by this research offers a solid, evidence-based basis to academic research and business decision-making in the swiftly changing realm of AI-based marketing.

7. Recommendations, Limitations and Scope of Future Study

7.1. Recommendations for Marketing Practitioners and Organizations

Invest in Trust Infrastructure: Organizations deploying AI marketing must prioritise the development of transparent data governance frameworks. This includes clear, consumer friendly privacy notices, granular data consent mechanisms, and regular communications about how personal data is used to improve the consumer experience. The strong negative correlation between privacy concerns and trust ($r = -0.54$) suggests that trust-building investments will yield measurable improvements in consumer engagement and conversion.

Adopt Participatory Personalization Design: Following the recommendations of Ramaswamy and Ozcan (2018), platforms should empower consumers to actively shape their personalisation preferences through explicit feedback mechanisms, preference centres, and data-sharing dashboards. This approach addresses both the autonomy dimension of trust and the relevance dimension of personalisation quality, creating a virtuous cycle of engagement and insight.

Differentiate AI Roles Between Transactional and Relational Contexts: Given the lower impact of AI on brand relationship quality, organisations should deploy AI for transactional optimisation (recommendations, pricing, logistics) while maintaining human-led or humansupplemented interactions for relational touchpoints (complaint resolution, loyalty recognition, high-value customer management). Hybrid human–AI service models that leverage the strengths of both are likely to optimise the satisfaction–relationship quality balance.

Develop Age-Stratified AI Personalisation Strategies: The significant age gradient in AI personalisation response argues for differentiated strategies tailored to younger (18–34) and older (45+) consumer segments. Younger consumers may respond to feature-rich, AI-intensive personalisation; older consumers may require simpler, more transparent, and more human mediated personalisation approaches.

Leverage Social Proof and Contextual Trust Signals: Given the cultural salience of interpersonal trust in the Indian context, AI recommendations should be augmented with social proof elements—ratings from trusted community members, endorsed by recognisable

figures, or validated by expert reviewers—to bridge the gap between algorithmic and interpersonal recommendation credibility.

7.2. Recommendations for Policymakers and Regulators

Accelerate DPDPA Implementation and Consumer Education: The study confirms significant consumer awareness of data privacy issues but limited understanding of specific rights under India's DPDPA 2023. Policymakers should prioritize consumer education campaigns that translate legislative protections into practical, actionable knowledge. Regulators should mandate clear, standardized consent disclosures in AI marketing contexts.

Establish AI Marketing Accountability Standards: Building on the principles of Trustworthy AI (Floridi et al., 2018), regulators should develop sector-specific accountability standards for AI marketing, including requirements for algorithmic transparency, data minimization, and redress mechanisms for consumers who experience harm from AI-driven decisions.

While this study makes a meaningful empirical contribution to the understanding of AI in personalised marketing, several limitations must be acknowledged in the interest of rigorous interpretation.

Sample Size and Representativeness: The sample of 150 respondents, while adequate for descriptive and correlational analyses, limits the statistical power of inferential tests and restricts generalisation to the broader Indian consumer population. In particular, the sample's skew towards younger, more highly educated, and urban respondents may not adequately represent Tier-III and rural Indian consumers, who are the next frontier of digital market growth.

Sampling Bias: The convenience and snowball sampling methodology may introduce systematic biases related to network effects—respondents recruited through social media and professional networks may share similar technological attitudes and digital literacy levels, reducing the diversity of perspectives captured. Future studies should employ stratified random sampling to ensure demographic representativeness.

Self-Report Limitations: The reliance on self-reported Likert-scale responses introduces the possibility of social desirability bias—respondents may underreport privacy concerns or

overstate purchase intention to appear technologically progressive. Behavioural data from actual platform interactions would provide more objective validation of self-reported attitudes. Cross-Sectional Design: The cross-sectional nature of the study captures a snapshot of consumer attitudes at a single point in time, preventing the assessment of how attitudes and behaviors' evolve as AI personalization capabilities advance and as regulatory frameworks like DPDPA 2023 are implemented. A longitudinal design would be more appropriate for studying the dynamic relationship between AI marketing development and consumer trust.

Limited Scope of AI Tools: The study focuses primarily on recommendation systems and chatbots, which represent the most common AI marketing tools at present. Emerging AI applications—including generative AI-powered content, virtual reality personalisation, and AI-driven dynamic pricing—are not covered, limiting the forward-looking applicability of the findings.

The findings and limitations of this study identify several productive directions for future research that would substantially advance the theoretical and empirical understanding of AI in personalized marketing.

First, longitudinal studies tracking the evolution of consumer trust, privacy perceptions, and AI engagement over time would provide invaluable insights into how these attitudes develop and stabilise as AI marketing matures and regulatory frameworks take effect. Such studies would be particularly timely given India's implementation of the DPDPA 2023.

Second, experimental research employing actual AI recommendation exposures and behavioural tracking (click-through rates, conversion rates, dwell time) would provide more objective measures of AI personalisation effectiveness than self-reported survey data, enabling causal inference about the mechanisms underlying purchase intention and satisfaction.

Third, the study's urban, educated sample leaves significant gaps in understanding the AI marketing experience of Tier-III, rural, and lower-income Indian consumers—populations that are the subject of major platform expansion strategies and whose digital literacy and trust dispositions may differ substantially from those of the urban cohort studied here.

Fourth, the role of cultural variables—including collectivism/individualism, uncertainty avoidance, and power distance—in moderating AI personalisation acceptance across India's diverse regional and linguistic communities represents an important area for culturally nuanced investigation. India's linguistic diversity (22 scheduled languages) also creates opportunities for research into the effectiveness of AI personalisation in vernacular languages.

Fifth, as generative AI (GenAI) technologies—including large language model-powered chatbots, AI-generated personalised content, and dynamic AI avatars—become commercially deployed in marketing contexts, their distinct effects on trust, satisfaction, and purchase behaviour warrant dedicated empirical investigation.

Sixth, the privacy paradox identified in this study—high engagement despite high privacy concerns—merits deeper psychological investigation. Research drawing on behavioural economics and cognitive dissonance theory could illuminate the cognitive mechanisms that allow consumers to reconcile their privacy values with their digital engagement behaviours, and identify intervention points that could help consumers make more autonomy-preserving choices

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Conflict of Interest/Competing Interests

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Data Availability

The raw data supporting the findings of this research paper will be made available by the authors upon a reasonable request.

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