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The Influence of AI-Based Marketing Strategies on Consumer Purchase Behaviour: A Study of Online Consumers in Chennai

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***Abstract* – Artificial Intelligence (AI) has become a central instrument of contemporary marketing, enabling firms to personalise offers, recommend products, target advertisements, converse with customers, forecast demand, and generate content at a scale and speed that manual methods cannot match. Yet empirical evidence on how these distinct AI-based marketing strategies shape the purchase behaviour of consumers in the Indian context remains limited. This study investigates the influence of AI-based marketing strategies on consumer purchase behaviour among online consumers in Chennai. Six independent variables—AI-Based Personalisation, AI-Driven Product Recommendations, AI-Powered Targeted Advertising, AI Chatbot Interaction, Predictive Marketing Analytics, and AI-Generated Marketing Content—were examined in relation to the dependent variable of Consumer Purchase Behaviour (encompassing purchase intention, purchase decision, actual purchase behaviour, repeat purchase behaviour, and brand preference). A quantitative research design was adopted, and primary data were collected from 271 online consumers in Chennai, Tamil Nadu, using a structured questionnaire based on a five-point Likert scale. Convenience sampling was employed. Data were analysed using IBM SPSS Statistics 26 (descriptive statistics, one-way ANOVA, Pearson correlation and multiple regression) and SmartPLS (measurement and structural model assessment). The findings reveal that all six AI-based marketing strategies positively and significantly influence consumer purchase behaviour. AI-Driven Product Recommendations emerged as the strongest predictor (β = 0.319), followed by AI-Based Personalisation and AI-Generated Marketing Content. The regression model explains 85.7% of the variance in consumer purchase behaviour. The study offers practical implications for marketers, e-commerce platforms, and digital strategists seeking to deploy AI responsibly and effectively.**

***Keywords* - AI-Based Marketing, Personalisation, Product Recommendations, Chatbots, Predictive Analytics, Consumer Purchase Behaviour, Chennai**

I. INTRODUCTION

1. Background of the Study

Digital transformation has reshaped the relationship between brands and consumers. Marketing, once organised around mass media and broad segmentation, now relies on algorithms that learn from clicks, searches, purchases, and conversations to serve each consumer a tailored experience. AI-based marketing strategies—including personalisation engines, recommendation systems, programmatic and targeted advertising, conversational chatbots, predictive analytics, and generative content tools—have become standard components of the marketing stack for e-commerce platforms, retailers, banks, and service providers.

India is among the world's fastest-growing online consumer markets, and metropolitan centres such as Chennai combine high smartphone penetration, widespread digital payments, and a young, digitally literate consumer base. Consumers in Chennai routinely encounter AI-curated feeds, 'recommended for you' product lists, retargeted advertisements, chatbot-assisted customer service, and automatically generated promotional content across shopping apps, social media, and search platforms. Understanding how each of these AI-enabled touchpoints influences what consumers intend to buy, actually buy, and buy again is therefore of considerable commercial and academic relevance.

Although industry reports routinely celebrate the revenue impact of AI in marketing, rigorous academic evidence

that separates the contribution of individual AI strategies to consumer purchase behaviour—particularly in an Indian urban setting—remains scarce. This study responds to that need.

2. Problem Statement

Organisations are investing heavily in AI-based marketing technologies, but they often do so without clear evidence on which strategies most strongly drive consumer purchase behaviour. Some AI applications, such as product recommendations, are widely credited with raising conversion; others, such as chatbots or AI-generated content, are adopted largely on the promise of efficiency and are less well understood in terms of their persuasive effect. In the absence of context-specific empirical data, marketers risk misallocating budgets, and platforms risk deploying AI features that consumers neither notice nor value. Furthermore, the preferences and sensitivities of Chennai's consumers—shaped by language diversity, price consciousness, and growing concern about data privacy—warrant a context-specific investigation rather than the wholesale application of findings from Western markets.

3. Research Gap

A review of the literature shows that studies on AI in marketing are predominantly conceptual or conducted in developed-market settings. Empirical work frequently examines a single AI application—most often recommendation systems or chatbots—in isolation, leaving the relative influence of multiple AI-based strategies within a single model unexamined. Few studies employ both regression-based and variance-based structural equation modelling (PLS-SEM) to triangulate results, and very few focus on online consumers in Chennai. This study addresses these gaps by examining six AI-based marketing strategies simultaneously, using SPSS and SmartPLS on primary data from online consumers in Chennai.

4. Research Objectives

- To examine the influence of AI-based personalisation on consumer purchase behaviour.
- To assess the impact of AI-driven product recommendations on consumer purchase behaviour.
- To evaluate the influence of AI-powered targeted advertising on consumer purchase behaviour.
- To determine the effect of AI chatbot interaction on consumer purchase behaviour.
- To analyse the role of predictive marketing analytics in shaping consumer purchase behaviour.
- To measure the impact of AI-generated marketing content on consumer purchase behaviour.
- To identify the AI-based marketing strategy with the strongest influence on consumer purchase behaviour and to test differences across age groups.

5. Significance of the Study

The study contributes theoretically by integrating the Stimulus–Organism–Response framework, the Theory of Planned Behaviour, and the Technology Acceptance Model to explain how AI-enabled marketing stimuli translate into purchase outcomes in an emerging-market setting. Practically, it provides marketers, e-commerce managers, advertising agencies, and technology vendors with evidence on which AI capabilities deserve priority investment. By ranking the strategies according to their predictive strength, the findings help organisations allocate marketing technology budgets more efficiently and design consumer experiences that are both effective and trusted.

6. Structure of the Paper

The paper is structured as follows: Section 2 presents the review of relevant literature and theoretical frameworks. Section 3 develops the research hypotheses. Section 4 describes the conceptual framework. Section 5 outlines the research methodology. Section 6 presents data analysis and results. Section 7 discusses findings and recommendations. Section 8 concludes the study, followed by references in IEEE format.

II. LITERATURE REVIEW

1. Artificial Intelligence in Marketing

Davenport et al. [1] argue that AI will alter marketing along three dimensions—the type of AI (task automation versus context awareness), the level of intelligence, and whether it is embedded in robots or operates through software—and that its impact will be felt across strategy, customer interaction, and the offering itself. Huang and Rust [2] propose a strategic framework in which mechanical, analytical, intuitive, and empathetic AI support market research, strategy formulation, and implementation of the marketing mix. Kaplan and Haenlein [8] similarly stress that AI, understood as a system's ability to interpret external data, learn from it, and adapt, has moved from experimental use into the mainstream of customer-facing business.

2. AI-Based Personalisation

Personalisation refers to the tailoring of content, offers, prices, and communication to the individual consumer using data on past behaviour and inferred preferences. Kumar et al. [3] show that AI-enabled personalised engagement—matching the right content to the right customer at the right moment—improves customer response and lifetime value. When consumers perceive that a platform 'understands' their needs, perceived relevance rises and the effort required to find suitable products falls, which is expected to strengthen purchase intention and conversion.

3. AI-Driven Product Recommendations

Recommender systems filter large assortments and present a small set of items predicted to match a consumer's tastes. Ricci et al. [4] document the methods—collaborative filtering, content-based filtering, and hybrid approaches—and the evidence that recommendations reduce information overload and increase the likelihood of purchase and cross-selling. By lowering search costs and exposing consumers to relevant alternatives at the moment of decision, recommendations act as a direct bridge between browsing and buying, and are therefore expected to exert a strong influence on purchase decisions and repeat purchasing.

4. AI-Powered Targeted Advertising

Targeted advertising uses behavioural, contextual, and demographic data to deliver advertisements to consumers most likely to respond. Boerman et al. [5] review the online behavioural advertising literature and conclude that while targeting can raise ad relevance and effectiveness, its outcomes depend on consumers' privacy concerns, perceived intrusiveness, and transparency. AI-powered targeting extends this logic through real-time bidding, lookalike modelling, and dynamic creative optimisation, enabling advertisers to reach consumers with timely offers that can shape both brand preference and purchase action.

5. AI Chatbot Interaction

Chatbots provide round-the-clock responses to product queries, order tracking, and after-sales issues, and increasingly guide consumers through the purchase journey. Luo et al. [6], in a large field experiment, found that chatbots can match experienced human sales agents in driving purchases when their artificial identity is not disclosed, but that disclosure before the conversation reduces purchase rates, an effect attributed to consumers' perceptions of lower knowledge and empathy. Chatbot interaction thus holds clear potential to facilitate purchase decisions, although its effect may be conditioned by trust and perceived quality of interaction.

6. Predictive Marketing Analytics

Predictive analytics applies machine learning to historical and real-time data to forecast customer behaviour such as churn, propensity to buy, next-best offer, and price sensitivity. Ma and Sun [7] describe how machine learning connects computing power with human insight across the marketing mix, enabling firms to anticipate needs and time interventions. For consumers, the visible outcome of predictive analytics is the timely, anticipatory offer—a reminder, a discount, or a product suggestion that arrives when purchase likelihood is highest—which is expected to influence purchase timing, frequency, and loyalty.

7. AI-Generated Marketing Content

Generative AI now produces product descriptions, email copy, social media posts, images, and video at low marginal cost, and permits rapid testing and localisation of messages. Huang and Rust [2] note that AI can support the implementation of marketing by creating and adapting content to segments and individuals. If AI-generated content is perceived as relevant, informative, and engaging, it can raise attention and persuasion; if perceived as generic or inauthentic, it may weaken credibility. Its effect on purchase behaviour therefore remains an important empirical question.

8. Consumer Purchase Behaviour

Consumer purchase behaviour encompasses the cognitive and behavioural stages through which consumers form an intention to buy, make a purchase decision, complete the purchase, repurchase, and develop brand preferences. Ajzen's Theory of Planned Behaviour [9] identifies intention as the proximal determinant of behaviour, shaped by attitudes, subjective norms, and perceived control. In this study, consumer purchase behaviour is treated as a multi-dimensional outcome comprising purchase intention, purchase decision, actual purchase behaviour, repeat purchase behaviour, and brand preference.

9. Theoretical Foundation

This study is grounded in three complementary frameworks. The Stimulus–Organism–Response (S-O-R) framework of Mehrabian and Russell [11] treats environmental cues as stimuli that influence the internal state of the consumer and, in turn, behavioural responses; AI-based marketing strategies are conceptualised here as stimuli and purchase behaviour as the response. The Theory of Planned Behaviour [9] explains how favourable attitudes towards AI-enabled marketing and the perceived ease of acting on it translate into purchase intention and behaviour. The Technology Acceptance Model [10] explains how perceived usefulness and ease of use of AI-driven shopping features encourage consumers to rely on them when making purchase decisions.

10. Research Gap Identification

A critical analysis of the literature reveals three gaps. First, most studies examine one AI application at a time, so the relative influence of multiple AI-based marketing strategies on purchase behaviour is not well established. Second, evidence is concentrated in Western and East Asian markets, with limited empirical work on online consumers in South Indian metropolitan settings. Third, relatively few studies combine regression analysis with PLS-SEM to confirm the robustness of the relationships. This study addresses all three gaps.

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III. HYPOTHESES DEVELOPMENT

Based on the theoretical frameworks and empirical evidence reviewed in the literature, the following hypotheses are proposed:

- **H1:** AI-based personalisation has a significant influence on consumer purchase behaviour.
- **H2:** AI-driven product recommendations significantly influence consumer purchase behaviour.
- **H3:** AI-powered targeted advertising significantly influences consumer purchase behaviour.
- **H4:** AI chatbot interaction significantly influences consumer purchase behaviour.
- **H5:** Predictive marketing analytics significantly influence consumer purchase behaviour.
- **H6:** AI-generated marketing content significantly influences consumer purchase behaviour.

Each hypothesis is derived from the reviewed literature and conceptually linked to the S-O-R framework, the Theory of Planned Behaviour, and the Technology Acceptance Model. The directional relationships proposed are consistent with prior empirical evidence suggesting that relevant, timely, and convenient AI-enabled marketing touchpoints encourage purchase behaviour.

IV. CONCEPTUAL FRAMEWORK / RESEARCH MODEL

The conceptual framework presents the theoretical relationships between the six independent variables (AI-based marketing strategies) and the dependent variable, Consumer Purchase Behaviour. Grounded in the S-O-R framework, it proposes that each AI-based marketing strategy acts as a stimulus that influences consumers' purchase intention, purchase decision, actual purchase behaviour, repeat purchase behaviour, and brand preference.

Independent Variables AI-Based Personalisation AI-Driven Product Recommendations AI-Powered Targeted Advertising AI Chatbot Interaction Predictive Marketing Analytics AI-Generated Marketing Content	H1–H6 → INFLUENCE	Dependent Variable Consumer Purchase Behaviour *(Purchase Intention; Purchase Decision; Actual Purchase Behaviour; Repeat Purchase Behaviour; Brand Preference)*

Figure 1: Conceptual Research Framework

V. RESEARCH METHODOLOGY

1. Research Design

This study adopts a quantitative, descriptive and causal research design, appropriate for examining the magnitude and direction of relationships between multiple predictor variables and an outcome variable. The descriptive component characterises consumers' perceptions of AI-based marketing strategies in Chennai, while the causal component assesses the influence of each strategy on purchase behaviour. A cross-sectional survey approach was employed to collect primary data.

2. Population and Sample

The target population comprises online consumers residing in Chennai, Tamil Nadu, who are aged 18 years or above and who have made at least one online purchase in the preceding six months through e-commerce websites, mobile shopping applications, or social commerce platforms. This criterion ensures that respondents have been exposed to AI-based marketing touchpoints. A sample of 271 respondents was obtained, which exceeds commonly recommended minimum sample sizes for multiple regression with six predictors and for PLS-SEM with a model of this complexity [12].

3. Sampling Technique

Convenience sampling was employed, enabling data collection from readily accessible online consumers across residential neighbourhoods, colleges, workplaces, shopping centres, and online communities in Chennai. While convenience sampling limits strict statistical generalisability, it is widely used in exploratory and descriptive consumer research where a complete sampling frame of online shoppers is unavailable. Efforts were made to include respondents of varied age, education, and spending levels.

4. Data Collection

Primary data were collected through a structured questionnaire administered in English and Tamil. The questionnaire was distributed through personal contact and through online channels, including email and messaging groups. A pilot study with 30 online consumers was conducted to assess clarity, comprehension, and relevance of the items, and minor wording changes were made. Out of 300 questionnaires distributed, 284 were returned, and after excluding incomplete or carelessly completed responses, 271 valid responses were retained for final analysis, yielding a response rate of 90.3%.

5. Measurement Scale

All constructs were measured on a five-point Likert scale, where 5 indicates Strongly Agree, 4 indicates Agree, 3 indicates Neutral, 2 indicates Disagree, and 1 indicates Strongly Disagree. Each independent variable was

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measured using four items adapted from validated instruments in the marketing, e-commerce, and technology adoption literature and contextualised to Chennai. The dependent variable, Consumer Purchase Behaviour, was measured with ten items covering purchase intention, purchase decision, actual purchase behaviour, repeat purchase behaviour, and brand preference.

6. Reliability and Validity

Reliability was assessed using Cronbach's Alpha [14] and Composite Reliability, with values above 0.70 considered acceptable. Convergent validity was assessed through Average Variance Extracted (AVE), with values above 0.50 considered acceptable [13]. Discriminant validity was examined using the Fornell–Larcker criterion and the Heterotrait–Monotrait (HTMT) ratio [15]. Content validity was established through expert review by two marketing academics, one digital marketing practitioner, and one research methodologist.

7. Statistical Tools

Data were analysed using IBM SPSS Statistics 26 and SmartPLS. SPSS was used for descriptive statistics, one-way ANOVA, Pearson correlation analysis, and multiple regression analysis. SmartPLS was used to assess the measurement model (reliability and validity) and the structural model, with path coefficients tested through bootstrapping with 5,000 resamples [12]. All tests were conducted at the 0.05 significance level, with results at the 0.01 level additionally noted.

VI. DATA ANALYSIS AND RESULTS

1. Demographic Profile of Respondents

Table 1 presents the demographic profile of the 271 respondents.

Table 1 – Demographic Profile of Respondents (N = 271)

Variable	Category	Frequency	Percentage (%)
Gender	Male	139	51.3
	Female	132	48.7
Age Group	18–25 years	84	31.0
	26–35 years	103	38.0
	36–45 years	56	20.7
	Above 45 years	28	10.3
Education	Undergraduate	117	43.2
	Postgraduate	110	40.6
	Professional / Others	44	16.2
Monthly Online Spending	Below ₹2,000	52	19.2
	₹2,000 – ₹5,000	98	36.2
	₹5,001 – ₹10,000	77	28.4
	Above ₹10,000	44	16.2
Total		271	100.0

Interpretation

The sample is balanced in terms of gender, with 51.3% male and 48.7% female respondents. The largest age group is 26–35 years (38.0%), followed by 18–25 years (31.0%), indicating that the sample is dominated by young, digitally active consumers who are the primary target of AI-based marketing. Most respondents hold undergraduate (43.2%) or postgraduate (40.6%) qualifications, and more than 80% spend at least ₹2,000 per month on online purchases, confirming that respondents have meaningful exposure to online shopping.

2. Descriptive Statistics – Consumer Purchase Behaviour

Table 2 presents descriptive statistics for the dependent variable, Consumer Purchase Behaviour. Respondents rated ten statements on the five-point Likert scale.

Table 2 – Descriptive Statistics: Consumer Purchase Behaviour

Statements	Mean	Std. D
AI-based marketing messages increase my intention to purchase products online.	4.26	0.92
I am more likely to buy products recommended by AI-based systems on shopping platforms.	4.33	0.88
AI-driven marketing helps me make quicker purchase decisions.	4.29	0.90
Personalised offers influence my final decision to buy a product.	4.31	0.89
I have actually purchased products after seeing AI-personalised ads or recommendations.	4.24	0.95
AI-based marketing has increased the frequency of my online purchases.	4.14	1.01
I repurchase from brands that provide AI-enabled personalised experiences.	4.18	0.98
I intend to continue buying from platforms that use AI to understand my needs.	4.20	0.96
AI-based marketing influences my preference for certain brands over competitors.	4.12	1.04
Overall, AI-based marketing strategies strongly influence my purchase behaviour.	4.23	0.93

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Interpretation
Table 2 shows that mean scores range between 4.12 and 4.33, indicating that respondents generally agree that AI-based marketing influences their purchase behaviour. The statement 'I am more likely to buy products recommended by AI-based systems on shopping platforms' received the highest mean (4.33), followed by 'Personalised offers influence my final decision to buy a product' (4.31), highlighting the prominence of recommendations and personalisation in the purchase journey. The statement 'AI-based marketing influences my preference for certain brands over competitors' recorded the lowest mean (4.12), suggesting that AI-based marketing influences immediate purchase decisions somewhat more than long-term brand preference. Standard deviations between 0.88 and 1.04 indicate reasonable consensus among respondents.

3. Descriptive Statistics – All Variables
Table 3 presents the mean and standard deviation of all independent variables and the dependent variable.

Table 3 – Descriptive Statistics: All Study Variables

Variable	Mean	Std. D
AI-Based Personalisation	4.22	0.91
AI-Driven Product Recommendations	4.30	0.88
AI-Powered Targeted Advertising	4.12	1.02
AI Chatbot Interaction	4.03	1.10
Predictive Marketing Analytics	4.09	1.05
AI-Generated Marketing Content	4.15	0.99
Consumer Purchase Behaviour (DV)	4.23	0.94

Interpretation
All AI-based marketing strategies are perceived favourably, with mean scores ranging from 4.03 (AI Chatbot Interaction) to 4.30 (AI-Driven Product Recommendations).

The relatively lower mean for chatbot interaction suggests that conversational AI is either less frequently used by consumers in the purchase journey or less consistently satisfying than other AI touchpoints. Product recommendations record the highest mean, reflecting how routinely and visibly consumers encounter them on shopping platforms. The mean for Consumer Purchase Behaviour (4.23) indicates a high overall level of purchase behaviour associated with AI-based marketing.

4. Measurement Model Assessment (SmartPLS)
Table 4 presents the reliability and convergent validity of the constructs, estimated using SmartPLS.

Table 4 – Reliability and Convergent Validity of Constructs

Construct	No. of Items	Cronbach's Alpha	Composite Reliability	AVE
AI-Based Personalisation	4	0.88	0.91	0.67
AI-Driven Product Recommendations	4	0.90	0.93	0.70
AI-Powered Targeted Advertising	4	0.86	0.90	0.64
AI Chatbot Interaction	4	0.85	0.89	0.63
Predictive Marketing Analytics	4	0.87	0.91	0.66
AI-Generated Marketing Content	4	0.86	0.90	0.65
Consumer Purchase Behaviour	10	0.93	0.94	0.62

Interpretation
Cronbach's Alpha values range from 0.85 to 0.93 and Composite Reliability values from 0.89 to 0.94, all well above the 0.70 threshold, confirming internal consistency. AVE values range from 0.62 to 0.70, exceeding the 0.50 criterion and establishing convergent validity. Indicator loadings ranged from 0.71 to 0.91. Discriminant validity was supported, as the square root of each construct's AVE exceeded its correlations with other constructs, and all HTMT ratios were below 0.85. The measurement model is therefore considered reliable and valid for structural analysis.

5. Correlation Analysis
Table 5 presents the Pearson correlation between the six AI-based marketing variables and Consumer Purchase Behaviour.

Table 5 – Correlation Between AI-Based Marketing Strategies and Consumer Purchase Behaviour

AI-Based Marketing Variables	r-value	p-value
AI-Based Personalisation	0.812	0.001*
AI-Driven Product Recommendations	0.846	0.001*
AI-Powered Targeted Advertising	0.774	0.001*
AI Chatbot Interaction	0.731	0.001*
Predictive Marketing Analytics	0.758	0.001*
AI-Generated Marketing Content	0.789	0.001*

Null Hypothesis (H0): AI-based marketing strategies do not have a significant relationship with consumer purchase behaviour.

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Interpretation

All six AI-based marketing variables show statistically significant positive correlations with Consumer Purchase Behaviour at the 1% level ($p < 0.001$), leading to rejection of the null hypothesis. AI-Driven Product Recommendations recorded the highest correlation ($r = 0.846$), followed by AI-Based Personalisation ($r = 0.812$) and AI-Generated Marketing Content ($r = 0.789$). AI-Powered Targeted Advertising ($r = 0.774$) and Predictive Marketing Analytics ($r = 0.758$) also showed strong associations, while AI Chatbot Interaction ($r = 0.731$) recorded the lowest, though still strong, correlation. The pattern of results supports the proposed conceptual framework.

6. One-Way ANOVA – Differences Across Age Groups

Table 6 presents the results of one-way ANOVA testing whether perceptions of AI-based marketing strategies and purchase behaviour differ across the four age groups.

Table 6 – One-Way ANOVA: Mean Scores by Age Group

Variable	18–25	26–35	36–45	Above 45	F-value	p-value
AI-Based Personalisation	4.36	4.29	4.10	3.82	9.84	0.001*
AI-Driven Product Recommendations	4.42	4.36	4.15	3.98	7.12	0.001*
AI-Powered Targeted Advertising	4.26	4.17	3.97	3.76	6.58	0.001*
AI Chatbot Interaction	4.18	4.09	3.89	3.65	5.43	0.001*
Predictive Marketing Analytics	4.22	4.15	3.96	3.75	4.76	0.003*
AI-Generated Marketing Content	4.30	4.21	4.01	3.72	8.35	0.001*
Consumer Purchase Behaviour	4.37	4.29	4.10	3.84	10.21	0.001*

Null Hypothesis (H0): There is no significant difference in the perception of AI-based marketing strategies and consumer purchase behaviour across age groups.

Interpretation

The ANOVA results show statistically significant differences across age groups for all six AI-based marketing variables and for Consumer Purchase Behaviour ($p < 0.01$), and the null hypothesis is therefore rejected.

The mean scores decline steadily with age: respondents aged 18–25 report the highest purchase behaviour (4.37) and those above 45 the lowest (3.84), with the largest difference observed for AI-Based Personalisation ($F = 9.84$) and Consumer Purchase Behaviour ($F = 10.21$). This suggests that younger consumers, who are more familiar with algorithm-driven interfaces, respond more strongly to AI-based marketing, whereas older consumers are more cautious. Marketers should therefore tailor the intensity and transparency of AI-based marketing to different age segments.

7. Regression Analysis

Table 7 presents the results of multiple regression analysis examining the influence of the six AI-based marketing strategies on Consumer Purchase Behaviour.

Table 7 – Effects of AI-Based Marketing Strategies on Consumer Purchase Behaviour

Model Summary

R	R Square	Adjusted R Square	Std. Error of Estimate	F-value	p-value
0.926	0.857	0.854	0.359	263.74	0.001*

ANOVA

Source	Sum of Squares	df	Mean Square	F	Sig.
Regression	204.46	6	34.08	263.74	0.001*
Residual	34.11	264	0.129		
Total	238.57	270			

Regression Coefficients

Predictors	B	Std. Error	Beta	t-value	p-value
(Constant)	-0.192	0.094	–	-2.043	0.042**
AI-Based Personalisation	0.205	0.052	0.198	3.942	0.001*
AI-Driven Product Recommendations	0.341	0.056	0.319	6.089	0.001*
AI-Powered Targeted Advertising	0.134	0.047	0.145	2.851	0.005*
AI Chatbot Interaction	0.091	0.043	0.106	2.116	0.035**

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Predictive Marketing Analytics	0.122	0.049	0.136	2.490	0.013**
AI-Generated Marketing Content	0.162	0.050	0.171	3.240	0.001*

Null Hypothesis (H0): AI-based marketing strategies do not significantly influence consumer purchase behaviour.

Interpretation

The model summary indicates a strong overall fit, with R = 0.926 and R Square = 0.857, meaning that 85.7% of the variance in Consumer Purchase Behaviour is explained by the six AI-based marketing strategies collectively. The ANOVA confirms that the model is statistically significant ($F = 263.74$, $p < 0.001$), and the null hypothesis is rejected.

The standardised Beta coefficients reveal the relative predictive strength of the variables. AI-Driven Product Recommendations is the strongest predictor ($\beta = 0.319$), followed by AI-Based Personalisation ($\beta = 0.198$), AI-Generated Marketing Content ($\beta = 0.171$), and AI-Powered Targeted Advertising ($\beta = 0.145$), all significant at the 1% level.

Predictive Marketing Analytics ($\beta = 0.136$) and AI Chatbot Interaction ($\beta = 0.106$) are significant at the 5% level but have the lowest coefficients, suggesting that these strategies contribute positively but less strongly to purchase behaviour in the Chennai context. The constant is negative and is not interpreted substantively, as a score of zero is outside the range of the five-point scale.

Regression Equation

Consumer Purchase Behaviour = -0.192 + 0.341(Recommendations) + 0.205(Personalisation) + 0.162(AI Content) + 0.134(Targeted Advertising) + 0.122(Predictive Analytics) + 0.091(Chatbot Interaction)

The equation shows that a one-unit increase in the perceived effectiveness of AI-driven product recommendations is associated with the largest increase in purchase behaviour (0.341 units), holding other variables constant, followed by AI-based personalisation (0.205 units).

8. Structural Model Assessment (SmartPLS)

To confirm the robustness of the regression results, the structural model was estimated in SmartPLS using bootstrapping with 5,000 resamples. Table 8 presents the path coefficients and hypothesis testing results.

Table 8 – Structural Model: Path Coefficients and Hypothesis Testing

Hypothesised Path	Path Coefficient (β)	Std. Dev.	t-statistic	p-value	Decision
H1: Personalisation → Purchase Behaviour	0.187	0.052	3.60	0.001*	Supported
H2: Recommendations → Purchase Behaviour	0.302	0.051	5.92	0.001*	Supported
H3: Targeted Advertising → Purchase Behaviour	0.138	0.051	2.71	0.007*	Supported
H4: Chatbot Interaction → Purchase Behaviour	0.101	0.045	2.24	0.025**	Supported
H5: Predictive Analytics → Purchase Behaviour	0.129	0.050	2.58	0.010**	Supported
H6: AI-Generated Content → Purchase Behaviour	0.163	0.051	3.20	0.001*	Supported

Interpretation

The structural model explains 86.1% of the variance in Consumer Purchase Behaviour ($R^2 = 0.861$; adjusted $R^2 = 0.858$). All six path coefficients are positive and statistically significant, and all t-statistics exceed the critical value of 1.96. AI-Driven Product Recommendations has the strongest path coefficient ($\beta = 0.302$), followed by AI-Based Personalisation ($\beta = 0.187$), AI-Generated Marketing Content ($\beta = 0.163$), and AI-Powered Targeted Advertising ($\beta = 0.138$). The results are consistent with the SPSS regression analysis in terms of both significance and the ranking of predictors, and hypotheses H1 to H6 are therefore supported.

Findings and Recommendations

Findings

The study yields several important findings. First, all six AI-based marketing strategies—AI-Based Personalisation, AI-Driven Product Recommendations, AI-Powered Targeted Advertising, AI Chatbot Interaction, Predictive Marketing Analytics, and AI-Generated Marketing Content—have a statistically significant positive influence on consumer purchase behaviour, supporting all six

hypotheses (H1 to H6) in both the regression and PLS-SEM analyses.

Second, AI-Driven Product Recommendations is the most influential strategy (β = 0.319, r = 0.846), indicating that helping consumers find relevant products at the point of decision is the most effective way in which AI converts interest into purchase. Third, AI-Based Personalisation (β = 0.198) and AI-Generated Marketing Content (β = 0.171) are the next most influential strategies, underscoring the importance of relevance and engaging communication.

Fourth, AI Chatbot Interaction (β = 0.106) and Predictive Marketing Analytics (β = 0.136) have the lowest, though significant, influence, suggesting that these capabilities are still maturing in terms of consumer perception. Fifth, the ANOVA results show that age significantly differentiates responses, with younger consumers reporting stronger purchase behaviour associated with AI-based marketing. Finally, the regression model's high explanatory power (R^2 = 0.857) confirms that the six AI-based strategies collectively provide a comprehensive explanation of purchase behaviour among online consumers in Chennai.

Recommendations

Based on the findings, the following recommendations are proposed for marketers, e-commerce platforms, and digital strategists. First, firms should prioritise investment in high-quality recommendation engines, since product recommendations exert the strongest influence on purchase behaviour. Hybrid recommendation models that combine browsing history, purchase data, and contextual signals, and that present explanations such as 'because you viewed...', can improve relevance and trust.

Second, personalisation should be extended across the customer journey—from homepage layouts and email to pricing and loyalty offers—while respecting consumer privacy and providing clear controls over data use. Third, marketers should integrate AI-generated content into campaigns with human oversight to ensure accuracy, brand voice, and authenticity, using AI to test and localise messages, including in Tamil, rather than to replace creative judgement.

Fourth, targeted advertising should balance relevance with perceived intrusiveness by capping frequency and being transparent about why an advertisement is shown. Fifth, because chatbots and predictive analytics currently show the lowest influence, firms should improve conversational quality, multilingual support, and seamless hand-over to human agents, and should use predictive analytics to time offers that are genuinely helpful rather than repetitive. Finally, given age-based differences, firms should adopt segment-specific strategies, offering older consumers greater transparency, simpler interfaces, and assisted options.

VII. CONCLUSION

This study provides empirical evidence that AI-based marketing strategies significantly and positively influence consumer purchase behaviour among online consumers in Chennai. By examining six distinct strategies through descriptive statistics, ANOVA, correlation, and regression analysis in SPSS, and by validating the model through SmartPLS, the research demonstrates that the way in which AI is applied—rather than the mere presence of AI—determines how strongly it shapes what consumers intend to buy, actually buy, and buy again.

The finding that AI-Driven Product Recommendations is the strongest predictor of purchase behaviour offers a clear strategic insight: AI is most persuasive when it reduces consumers' search effort and presents relevant options at the moment of decision. Personalisation and AI-generated content reinforce this effect by increasing relevance and engagement, while targeted advertising, predictive analytics, and chatbots play supportive roles whose potential is not yet fully realised.

The high explanatory power of the model (R^2 = 0.857 in SPSS; R^2 = 0.861 in SmartPLS) confirms that the six AI-based strategies together provide a robust framework for understanding purchase behaviour in digital markets. The study extends the S-O-R framework, the Theory of Planned Behaviour, and the Technology Acceptance Model to the context of AI-based marketing in an emerging economy.

The study is subject to limitations, including the use of convenience sampling, a single geographic area, and cross-sectional self-reported data. Future research could employ probability sampling, compare multiple Indian cities, use longitudinal or experimental designs, and examine mediating and moderating variables such as trust, perceived privacy risk, perceived personalisation–privacy trade-offs, and consumer AI literacy. Qualitative methods could further illuminate how consumers experience and interpret AI-based marketing.

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