The Role of AI Recommendation Systems in Shaping FMCG Buying Behavior among Chennai Consumers

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Abstract

The study explores the impact of AI driven recommendation systems on FMCG purchase behaviour among consumers in online retailing in Chennai. With a sample size of two hundred, The study is quantitative, and employs regression, correlation, chi-square, t-test factor analysis SEM to explore linkages among AI personalization, trust engagement and consumer purchase intentions. The findings suggest that AI-based recommendation systems play a critical role in facilitating product discovery, building trust on the online platforms and impacting impulse buying. Tailoring and transparency represents two of the driving factors behind consumer adoption and satisfaction. We add to existing literature by providing empirically driven evidence for how AI recommendation features influence purchase behaviour in these settings. The implications are some recommendations based on the ethical, transparency and contextually adaptive recommendation strategies for retailers to achieve sustainable loyal consumers and beat competition. Limitations and implications for future research are addressed.

Keywords: Artificial Intelligence, Recommendation Systems, FMCG (Fast-Moving Consumer Goods), Consumer Behaviour, Online Retail

Introduction

The emergence of artificial intelligence (AI) has raised the bar for worldwide retail efforts and recommendation systems are at the vanguard of FMCG marketing advancements. In recent years, ecommerce consumers have been indigenous of a new wave in product interaction, purchasing decision and online engagement driven by personalized online interactions and seamless multiple stopover purchase experiences (Wang et al.,2346). In countries like India, the digitalisation is fostering substantial inroad of e-shopping where Chennai can be considered as a prime urban centre for technological transition and consumer variety (Alyahya, 2023; Zhou, 2024).

AI-oriented recommendation systems use complex algorithms - such as collaborative filtering, deep learning and hybrid models - to process browsing history and situational preferences (Sankranthi, 2025). The transition from simple 'customers who bought this also' recommendations to real-time, context-based personalization has brought measurable returns for retailers and consumers (JlassiKnable, 2025). Among other markets, the recommendation engine market is projected to grow to 3.47 billion U.S dollars in 2029 worldwide, suggesting its centrality as part of a digital strategy (Business Research Company 2025).

Behavioral research confirms that tailored product suggestions enhance purchase intention, satisfaction, and engagement (Rolando, 2025). Personalization, trust, and transparency — the three pillars of contemporary AI recommendations — are essential for building consumer confidence in digital platforms (AIRA, 2025; Wang et al., 2025). Region-specific studies in India, such as those by Alyahya (2023) and Sankranthi (2025), highlight how cultural factors, urbanization, and regional shopping trends modulate technology adoption and the efficacy of recommendation engines.

In the FMCG industry, which includes items that are purchased with higher frequency (food, drinks and household products), consumers use routine buying behaviour in decision making process which is fast and they are very responsive to promotion activities (M Alyahya, 2023). AI mechanisms are transformational surfacing relevant FMCG offers, predicting consumer needs and adapting to retrial for improved accuracy (IJSCI, 2025; Zhou, 2024).

Although AI recommendations are increasingly becoming popular, the literature finds some key factors which play a role in determining the consumer acceptance of these kind of technologies. Consumer confidence relies on transparent systems and perceived fairness, because if recommendation logic is opaque or targeting biased then consumer loyalty can be exposed (Wang, 2025; Rolando, 2025).Privacy and ethical considerations have come to the fore, prompting calls for best practices that ensure fairness and inclusivity in algorithmic design (Sankranthi, 2025; Business Research Company, 2025).

Research specifically carried out in the Indian context like Jharkhand and Chennai showed variance in AI adoption rate and acceptance (Recent Scientific, 2024; Alyahya, 2023). Urban citizens are in general more comfortable resigning control to ai-infused platforms, highlighting the significance of local approaches to algorithmic personalization (Rolando, 2025).

Beyond this, technological innovations such as generative AI, voice commerce and session-based recommendations are transforming consumer experiences, offering new opportunities and challenges for FMCG retailers (Jlassi, 2025; Wang et al., 2025). In this sense, the combination of behavioral economics, predictive analytics and real-time engagement tactics signal a new era in data-informed retailing (Sankranthi 2025; Zhou 2024).

This study is found at the intersection of AI, consumer behaviour, and urban Indian retail, seeking to develop upon existing models by empirically judging the impact of recommendation system features on FMCG purchase decisions in Chennai. By incorporating multiple forms of statistical analysis, the research aims to disclose psychological mechanisms and update practical strategies for digital commerce in India's fast-evolving disguise.

Literature Review

AI Recommendation System Fundamentals and Market Growth

AI-based recommendation engines have emerged as the primary component of personalized product suggestion technologies across online retail. According to the Business Research Company (2025), global investment in AI-powered systems has increased to $3.47 billion, with FMCG and retail sectors leading the adoption process. This investment reflects market trust in AI's ability to optimize user experiences and enhance profitability (Singhal & Kumar, 2025).

Personalization and Consumer Engagement

Personalization is one of the most popular technique as it considered to be a key factor in recommendation performance (Wang et al., 2025; Valencia-Arias et al., 2024). Solomon (2017) pointed out that opt-in recommendations increase consumer engagement by considering only browsing and purchase history. The deep learning models used in AI makes real time personalized recommendation algorithm possible, which can provides users content and results that are only contextually related than the actual query (Imaginea Technologies, 2024; Sankranthi, 2025).

Trust, Transparency, and User Acceptance

The extent of trust customers have in recommendation engines is formed to a great degree through perceived transparency and ethical treatment of personal data. Helpful relevant suggestions with transparent logic could have higher purchase intentions and repeat visits, but negative irrelevant or opaque recommendations can reduce loyalty (Rolando 2025). Valencia-Arias et al. (2024), a system is good, if the 'reasons' of suggestion can be understood by user and ultimately this would lead in increasing satisfaction and acceptability.

Impact of AI Recommendations on FMCG Impulse Purchases

FMCG is a fast-moving business as product turnover is always high. AI-based recommendations are particularly powerful, and they will lead to fast decision making and brand relatedness (IJCRT, 2025; Zhou, 2024). Chatterjee et al. (2023) then drew a direct relation between recommendation quality and conversion rates in FMCG e-commerce settings.

Session-based and Real-Time Recommendations

The evolution of recommendations is from collaborative filtering to session-based, real-time algorithms (Business Research Company, 2025; Sankranthi, 2025). State-of-the-art systems can serve 950K user interactions a second, resulting in significant gains on both user engagement and average session time (Journalijsra, 2025). Content generation and diversity of prompts have both been surpassed by generative AI as well (Superagi, 2025).

Regional Studies – India and Urban Consumer Patterns

Recent literature has touched on the regional context where studies in Jharkhand, Chennai and other urban areas identify digital literacy, infrastructural inequalities and unique consumer attitudes (Recent Scientific, 2024; Alyahya, 2023). Higher penetration of smartphones in metro cities also leads to the higher adoption of AI and online FMCG purchase (MeitY, 2021).

Predictive Analytics through Supply Chain Optimization

AI's predictive analytics facilitate effective inventory management, demand forecasting, and supply chain agility (Equitymaster, 2025; Singhal & Kumar, 2025). Indian retailers have experienced a decrease in overstocks/stockouts and better product quality which increases consumer satisfaction and the possibility of repeat sales.

Cultural and Ethical Issues

Cultural attitudes have been emphasized as mediating AI acceptance in several studies; ethical, user-focused AI development is now being required by regulators and other technology customers (Alyahya 2023; Rolando 2025). Chatterjee et al. (2023) People will tend to be loyal towards AI decision logic, especially when they believe that it is fair and inclusive.

Impact on Brand Loyalty and Long-Term Engagement

Recommendations affect both immediate purchase in the short and the long term loyalty to the brand (Nature, 2025). Frequent AI-powered recommendation exposure emphasizes long-lasting consumer relationships, particularly when the model adjusts to new preferences with time through data feedback loops (Valencia-Arias et al., 2024).

Recent Developments – Generative AI and Multimodal Systems

2025 The transition to generative adversarial and multimodal recommender systems After analyzing textual content data, image, video and voice input will focus on improving buying convenience (Superagi, 2025; Wang et al., 2025). These architectures offer immediate, hyper- personalized experiences and increased conversion rates, but also bring new concerns about privacy and data security.

Research Gap

While the growing use of AI-based recommendation systems has transformed and mediated consumer interactions in online retail globally (Sankranthi, 2025; Wang et al., 2025), there is limited empirical research that examines how they influence the purchase behaviour of FMCG products in an urban Indian context (Alyahya, 2023). Regional investigations show that uptake and impact are heterogeneous across demographic groups, but few systematically contrast major technology attributes — such as personalization, transparency, and session adaptation — between small city-level markets like Chennai (Recent Scientific, 2024; Business Research Company, 2025).

Previous research has investigated trust building and its satisfaction in the context of e-commerce (Rolando, 2025; Wang et al., 2025), but very little is known about psychological and contextual determinants for purchase decision making among Indian FMCG consumers. Functional recommendations engine problems (transparency, ethical fairness) have until recently received little focused attention and little quantita tive validation making much of the solutions unsound (Jlassi, 2025; Sankranthi, 2025).

Even the spectrum of culture, technology and behaviour for Chennai are quite different relative to those for global and pan-India studies – specifically in an environment like fast-moving FMCG (Alyahya, 2023). The inclusion of new technologies (e.g., generative AI, AR) also pose questions regarding emergent personalization and data-driven marketing (Business Research Company, 2025).

Therefore, there is a requirement for empirical evidence on the multi-dimensional impact of AI recommendation systems on FMCG purchase behavior among urban Indian consumers, using robust statistical analysis and relevant samples from specific regions. This paper fills this gap by integrating various analytical tools and the latest literature to provide practical insights.

Objectives

1. To examine the influence of AI-based recommendation system's characteristics (personalization, transparency and accuracy) on Purchase intention of FMCG goods through consumers in Chennai.
2. To investigate the role of consumer trust and involvement in explaining AI recommendations towards FMCG purchasing behaviour.
3. To investigate the demographic variations in acceptance AI based recommendations among Chennai consumers.

Hypotheses

- H1: AI recommendation system features positively influence FMCG purchase intention.
- H2: Trust and engagement mediate the relationship between recommendation systems and purchase behaviour.
- H3: There are significant demographic differences in consumer responses to AI-powered recommendations.

Methodology

Participants/Sample:

A sample of 200 online FMCG consumers from Chennai were chosen for the study through stratified random sampling in such a way that there was an equal representation of different demographic factors such as age, gender and income.

Data Collection:

Survey questionnaires were used to collect data about respondents' AI recommendation experiences, trust, engagement and demographic information as well as buying behaviour. Instruments were pilot tested and validated (Cronbach's alpha > 0.75).

Data Analysis:

- Regressing Effect of Recommendation Features on Purchase Intention.
- Correlation for trust/engagement and purchase behavior.
- Chi-square for demographic differences.
- Factor analysis for scale development/validation.
- test and one-way ANOVA for group differences.
- SEM was employed to test the mediation effect.

Results

Table 1: Descriptive Statistics

Variable	Mean	SD	Min	Max
Purchase Intention	3.85	0.64	1	5
Personalization	4.12	0.58	2	5
Trust	3.90	0.62	1	5

Interpretation

Table 1 depicts the central tendencies and distribution of major variables of online FMCG consumers in Chennai. Respondents generally have favorable attitudes toward AI recommendation features in e-commerce as reflected by a high mean score for personalization and purchase intention ($M = 4.12$, $M = 3.85$), which suggests that people are very open to shopping experiences based on artificial intelligence technology.

Table 2: Regression Analysis – Recommendation Features on Purchase Intention

Variable	Beta	t	p
Personalization	0.44	6.12	<0.001
Transparency	0.29	4.10	<0.001
Accuracy	0.32	5.03	<0.001

Interpretation

The regression analysis indicates that there are significant positive relationships between personalization ($\beta = 0.44$), transparency ($\beta = 0.29$) and accuracy ($\beta = 0.32$) with purchase intention ($P < 0.001$). These results verify Hypothesis 1, and suggest that the availability and quality of AI recommendation feature indeed motive consumer purchases with strong implications in FMCG.

Table 3: Correlation – Trust, Engagement, and Purchase Behaviour

Variable	r	p
Trust vs. Engagement	0.52	<0.001
Engagement vs. Purchase Intention	0.46	<0.001

Interpretation:

Trust has a strong positive relationship with engagement ($r = 0.52$) and engagement is positively correlated with purchase intention ($r = 0.46$), which support H2. Our findings indicate that trust in AI leads to more engagement and higher FMCG purchase intentions.

Table 4: Chi-Square – Demographic Differences in AI Adoption

Group	χ^2	p
Age	12.3	0.03
Gender	6.7	0.09
Income	15.8	0.01

Interpretation:

Chi-square tests indicate that there are significant differences among AI adoption in terms of age ($\chi^2 = 12.3$, $p=0.03$) and income level ($\chi^2 = 15.8$, $p=0.01$), but not with gender ($\chi^2 = 6.7$, $p=0.09$). This provides evidence that AI recommendation adherence is more affected by the socio-economic level and generation rather than gender, which to some extent supports hypothesis.

Table 5: Factor Analysis – Recommendation System Constructs

Factor	Loading
Personalization	0.81
Transparency	0.78
Accuracy	0.84
Trust	0.79
Engagement	0.76

Interpretation:

Loading factors higher than 0.75 provide strong evidence of the construct validity for the measurement scales of personalization, transparency, accuracy, trust and engagement. The findings support the reliability of the instrument to measure AI recommendation system attributes and user perceptions in this empirical setting.

Table 6: t-Test – Urban vs. Suburban User Experience

Group	Mean Diff.	t	p
Urban vs. Suburban	0.43	2.41	0.018

Interpretation:

There is a statistically significant difference in mean ratings ($t = 2.41$, $p = 0.018$) that urban users ranked AI recommendation functionality significantly higher than rural ones. This highlights the impact of urbanization on technology adoption and localization of marketing strategies.

Table 7: ANOVA – Buying Behaviour across Income Levels

Source	F	p
Income Level	3.98	0.021

Interpretation:

Statistical analysis with ANOVA shows buys' behavior varies significantly with income ($F = 3.98$, $p = 0.021$). Recommendation system discriminated by household income We observe more variation along the upper income bands, which is consistent with Jan et al (2008): higher-income households prone to possessing PCs and spending on fast-moving consumer goods.

Table 8: SEM – Mediation Analysis

Path	Estimate	p
Recommendation → Trust → Purchase Intention	0.24	<0.01
Recommendation → Engagement → Purchase Intention	0.18	<0.05

Interpretation:

In the structural equation model, trust (estimate = 0.24, p ;p > 0.05). This exhaustive examination of the factors underscores the complexity of consumer decision-making in FMCG e-commerce.

Table 9: Multiple Regression – All Predictors

Predictor	Beta	p
Personalization	0.31	<0.001
Transparency	0.14	0.034
Accuracy	0.21	0.005
Trust	0.28	<0.001
Engagement	0.16	0.019

Interpretation:

Each of personalization, transparency, accuracy, trust and engagement have a significant positive effect on the intention to buy ($p < 0.01$), with trust ($\beta = 0.28$) and personalization ($\beta = 0.31$) having the greatest impact. This holistic framing underlines the multifaceted complexity of consumer behavior in FMCG e-commerce.

Table 10: Summary of Key Outcomes by Demographic Segment

Segment	High Impact Feature	Purchase Intent	N
Youth	Personalization	High	62
Professionals	Accuracy	Moderate	53
Retirees	Trust	Moderate	17
Homemakers	Transparency	High	68

Interpretation:

Segmentation shows that youth and homemakers value personalization the most, whereas professionals - accuracy. These findings suggest a segmentalized AI-based approach to marketing for better engagement and conversion.

Discussion

We now have evidence of the pre-eminence of AI-embedded recommendation systems in influencing FMCG consumer choices within Chennai's digitally empowered market, consistent with macro-trends across India and international academic research (Sankranthi, 2025; Alyahya, 2023). By means of both regression and SEM findings, it is demonstrated that personalization, transparency and accuracy significantly predict purchase intention with trust and engagement enacted as significant mediators. Factor and reliability analysis confirm the constructs adopted in literature (Wang et al., 2025; Jlassi, 2025).

In line of Rolando (2025) and Recent Scientific (2024), urban consumers are more likely to accept and influence from AI recommendations, confirming the contribution of Digital Skills and Urban Tech Environment. The results are consistent with recent models of consumer decision-making in which algorithmic customization and explicit reasoning enhance satisfaction and conversion (Wang et al., 2025).

This demographic differentiating opens up avenues for tailored AI strategies: youth and homemakers are seen to be most receptive towards personalized as well transparent recommendations, like the trends observed by Alyahya (2023) and Sankranthi (2025). The income and urbanization related digital divide indicate additional opportunity for retailers to tailor outreach and reinforce inclusiveness (Recent Scientific, 2024).

Limitations—using survey data and a cross-sectional study design to explore qualitative measures, while suggestions of longitudinal and mixed-methods approaches have been made (Jlassi 2025; Sankranthi et al. In addition, the future studies could consider new emerging AI domains (for example, generative recommendation and AR) which have promising application features for emersion context-aware in shopping experiences (Business Research Company, 2025; Wang et al., 2025).

Taken together, the study provides empirical insights on understanding psychological and practical issues related to recommend systems in digital FMCG transactions which can inform both researchers as well as practitioners given growing market dynamics.

Implications

The study concludes with some strategic and operational implications for retailers and online marketeers. First, to provide contextually relevant product recommendations and increase conversion rates, investments need to be made into cutting edge AI recommendation engines specifically designed for urban markets like Chennai. Retailing managers could give preference to systems that enable transparency and customization, since these have been empirically shown to impact trust engagement and repeat purchasing behaviour (Wang et al., 2025; Rolando, 2025).

Second, algorithmic fairness and privacy should be embedded into recommendation design to ensure fair treatment of all customer groups. As the results indicate, the influences of demographic diversity go beyond both acceptance and perceived effectiveness—retailers should develop differentiated strategies for youth, homemakers, and professionals.

Third, continuous measurement of recommendation engine performance – using predictive analytics, customer surveys and sales statistics –will allow retailers to adjust their strategies and remain sensitive to changing consumer needs (Sankranthi, 2025; Business Research Company, 2025). A continued partnership with AI technology providers as well as ongoing consumer education will help fuel further acceptance and adoption.

Lastly, brands will need to be watchful of moral compasses and regulations that will pursue the fine balance between innovation and shielding citizens from potential harm. Open communication regarding data usage encourages trust and continued participation.

Conclusion

This research proves the strong established impact of AI recommendation systems on FMCG buying behavior in Chennai consumers. Personalization, transparency and accuracy function as a strong predictor of purchase intention, with trust as well as intension mediating technology and consumer effects. Demographics-based analysis also shows discrepancies in adoption and engagement, which call for personalized algorithmic approaches. This work fills a research gap to offer localized insights and redesigned multi-method analyses for today's digital context. For the future, retailers in urban Indian contexts must invest further in such adaptive ethical recommendation systems to sustain growth of FMCG e-commerce. Future research should additionally include longitudinal perspectives and advanced AI techniques, including generative and immersive AR technologies to gain further insights into consumer dynamics.

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