

AI-Driven Personalization versus Influencer Marketing: A Study on Gen Z Purchase Behaviour in Indian E-Commerce and Quick Commerce

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Abstract—This study examines the comparative influence of AI-driven personalization and influencer marketing on the purchase behavior of Generation Z consumers in India, with specific reference to Myntra (fashion e-commerce) and Blinkit (quick commerce). Using a mixed-methods research design, primary quantitative data was collected from 77 Gen Z respondents (ages 18–29) through a structured Likert-scale questionnaire and analyzed using Ridge and Lasso Regression, t-tests, ANOVA, mediation analysis (Sobel test), and Pearson correlation. The findings reveal that AI recommendation engines are the strongest predictor of impulse purchases ($r = 0.822$, $p < 0.001$), while micro-influencers enjoy significantly higher trust than celebrity endorsers ($t = 3.282$, $p < 0.01$). The mediation analysis demonstrates that AI does not replace influencer marketing but amplifies its effectiveness through precisely timed content delivery (Sobel $Z = 10.24$, $p < 0.001$). Furthermore, privacy discomfort does not significantly erode platform loyalty when tangible personalization benefits are perceived. The study contributes an integrated AI-Influencer Hybrid framework and offers actionable recommendations for Indian e-commerce platforms targeting the projected USD 100 billion Gen Z digital spend by 2030.

Key Terms—AI personalization, influencer marketing, Generation Z, e-commerce, quick commerce, Myntra, Blinkit, consumer behavior, India

I. INTRODUCTION

The Indian digital commerce landscape is undergoing a fundamental transformation, evolving from a nascent market into a massive ecosystem valued at approximately USD 90 billion. By 2025, the online shopping market in India has more than doubled in five years, with 290 to 300 million active online shoppers [1]. This growth is driven primarily by Generation Z (born mid-1990s to early 2010s), who now constitute 40% to 45% of all digital shoppers and account for nearly half of all new orders.

Unlike prior generations who viewed online shopping as a utilitarian activity for deal-finding and time-saving, Gen Z treats digital commerce as an expression of identity and a form of entertainment. This paradigm shift necessitates that e-commerce platforms transition from search-and-browse models to what may be termed "discovery commerce," where the boundaries between content consumption, community engagement, and shopping become increasingly blurred [2].

The Indian market presents unique complexities due to its linguistic diversity and the rapid growth of Tier-2 and Tier-3 cities. Two platforms exemplify contrasting approaches within this ecosystem: Myntra, India's leading fashion e-commerce platform, employs AI-powered tools such as the Maya conversational assistant, My Stylist feature, and virtual try-on capabilities to deliver personalized fashion experiences. Blinkit, the country's largest quick commerce platform, leverages AI through its Recipe Rover system and predictive inventory management to deliver groceries and essentials within 10 to 15 minutes [3].

Both platforms simultaneously invest heavily in influencer marketing, with India's influencer market valued at approximately INR 2,200 crore in 2024 and projected to reach INR 3,375 crore by 2026 at a 25% compound annual growth rate [4]. This dual investment raises a critical question: for Gen Z consumers, what drives purchase decisions more effectively—algorithmic precision or human creator influence?

This study addresses this question through a comparative empirical analysis, examining five research objectives: (1) the impact of AI personalization tools on purchase decisions and impulse buying; (2) the comparative effectiveness of micro-influencers versus celebrity endorsers in building brand trust; (3) consumer preferences for AI versus human influence

across product categories; (4) the synergistic effects of AI and influencers on engagement; and (5) the personalization-privacy trade-off and its impact on brand loyalty.

Table 1 presents the key market metrics that contextualize this research.

Table 1. Indian Digital Commerce Market Metrics

Metric	2024 Status	2026 Projection	Growth Driver
Online Shopper Base	230–250 million	300 million+	Tier 2+ City Adoption
Gen Z Market Share	~35%	45%	Digital Nativity
Quick Commerce Market	\$5–7 Billion	\$50 Billion	10-Minute Delivery
Influencer Market Size	₹2,200 Crore	₹3,375 Crore	25% CAGR
AI Adoption in Retail	45% (SMBs)	84% (E-comm)	Generative AI Integration

II. REVIEW OF LITERATURE

The theoretical foundations of this study draw from multiple streams of research spanning behavioral theories and digital marketing applications in Indian e-commerce.

A. Foundational Behavioral Theories

The Theory of Planned Behaviour by Ajzen (1991) posits that consumer behavior is determined by attitudes, subjective norms, and perceived behavioral control [5]. In the context of Indian e-commerce, influencer culture serves as a subjective norm while AI algorithms enhance perceived behavioral control by reducing decision friction. Gefen, Karahanna, and Straub (2003) established that trust in an online platform is as important as its perceived usefulness, a finding that remains relevant as consumers balance AI benefits against data surveillance risks [6].

B. The Rise of Algorithmic Personalization (2015–2020)

Eisenbeiss (2015) demonstrated that personalized advertisements can increase click-through rates by 30% when relevance and timing are optimized [7]. Martin and Murphy (2017) identified privacy concerns as a significant moderator, finding that excessive data collection can erode brand trust [8]. Grewal, Roggeveen, and Nordfalt (2017) confirmed that personalization enhances customer satisfaction and loyalty [9]. Jarek and Mazurek (2019) found that AI-based recommendations significantly increase purchase likelihood and engagement [10].

C. Pandemic-Era Shifts and Contemporary Research (2021–2026)

Christopher (2022) observed a marked increase in impulse buying among young Indian consumers who demanded rapid delivery, coinciding with Grofers rebranding as Blinkit [11]. Saleem and Bhandari (2022) confirmed that fast delivery increases both purchasing frequency and loyalty [12]. Shah, Asif, Mohd Saleem, and Bilal (2023) examined Myntra's use of AI for fashion trend prediction [13].

More recently, Mishra (2025) found that while AI influencers are effective for certain applications, human influencers remain superior for building trust [14]. Gerlich (2025) demonstrated category-specific differences, with AI outperforming humans for electronics recommendations while humans remain preferred for fashion and beauty [15]. Koneti (2025) found that AI can build consumer trust when deployed transparently and ethically [16]. Chaudhari and Udasi (2026) reported a 23% gap between metro and smaller cities in AI and quick commerce adoption [17].

D. Identified Research Gaps

Three critical gaps emerge from the literature: (1) a lack of integrated frameworks examining AI and influencers as complementary rather than competing forces; (2) over-concentration of research on metro cities and Western consumers, neglecting India's Tier-2 and Tier-3 markets; and (3) insufficient cross-category comparison between fashion e-commerce and quick commerce platforms. This study addresses all three gaps.

E. Research Problem

The broad research problem identified by me relates to the need to understand the relationship between the two forces, i.e., precision of algorithmic recommendation (AI) and authenticity of the humans (influencers).

F. Research Questions (RQs)

In line with your objectives, I have generated five research questions for this study as follows:

RQ1: Relates to the degree to which AI leads to impulsive purchase behavior.

RQ2: Considers the comparison between trust in micro-influencers and celebrities.

RQ3: Looks into differences based on city tier (Metro cities vs. Tier 2/3).

RQ4: Relates to the hybrid effect and its influence on platform loyalty.

RQ5: Concerns the Privacy Paradox in the context of data sharing.

Objectives of the study

- To determine how AI personalization tools like Myntra's Maya and Blinkit's Recipe Rover influence purchase decisions and trigger impulse buying through virtual try-ons and tailored recommendations.
- To evaluate whether influencer marketing builds brand trust for Myntra and Blinkit and how influencer effectiveness compares to that of regular individuals in driving engagement.
- To identify consumer preferences for AI versus human influence across product categories, such as AI for electronics and groceries versus influencers for fashion and beauty.
- To explore how AI and influencers work together to boost engagement, focusing on the effects of personalization and timing.
- To investigate the personalization–privacy trade-off, its effect on brand loyalty, and the business impact (cost savings and revenue) of AI-driven personalization and influencer marketing for Myntra and Blinkit.

III. THEORETICAL FRAMEWORK

The study integrates five theoretical models to construct a comprehensive analytical framework.

The Stimulus-Organism-Response (S-O-R) Model serves as the primary framework, where AI features and influencer content function as stimuli, Gen Z cognitive and affective states (trust, perceived relevance, emotional connection) constitute the organism, and purchase intention, impulse buying, and brand loyalty represent the response variables.

The Theory of Planned Behaviour (TPB) explains how influencers function as subjective norm reference groups, while AI tools enhance perceived behavioral control by reducing decision-making effort through features such as virtual try-ons and conversational assistants.

The Technology Acceptance Model (TAM) addresses Gen Z adoption of AI tools through perceived usefulness (e.g., Blinkit's Recipe Rover suggesting meals from available ingredients) and perceived ease of use (e.g., Myntra's vernacular language search supporting 12 Indian languages).

Privacy Calculus Theory frames the trade-off between personalization benefits (convenience, discounts) and privacy costs (data surveillance, targeted advertising), with trust as the mediating variable.

Finally, the study introduces the **AI-Influencer Hybrid Mechanism**, proposing that the most effective strategy uses AI to optimize influencer content delivery timing and audience matching, thereby meeting both functional needs (speed, accuracy) and emotional needs (community, inspiration) of Gen Z consumers.

IV. RESEARCH METHODOLOGY

A. Research Design

A quantitative methodology using survey-based data collection with a mixed-methods approach was adopted. Data was collected from 77 Gen Z respondents (ages 18–29) who are active users of Myntra and/or Blinkit, using a five-point Likert scale questionnaire (1 = Strongly Disagree to 5 = Strongly Agree).

B. Sampling and Demographic Profile

Stratified random sampling was employed with the following strata: age groups (18–21 years: 54.5%, 22–25 years: 26.0%, 26–29 years: 19.5%) and city tiers (Metro: 57.1%, Tier-2: 24.7%, Tier-3: 18.2%). Inclusion criteria required at least one purchase on Myntra or Blinkit in the preceding six months based on either an AI recommendation or influencer endorsement.

Table 1: Distribution by Age Group

Age Group (Years)	Percentage (%)
18–21	54.5
22–25	26.0
26–29	19.5
Total	100.0

Respondents by Age Group

Percentage distribution of respondents across age groups.



Table 2: Distribution by City Tier

City Tier	Percentage (%)
Metro	57.1
Tier-2	24.7
Tier-3	18.2
Total	100.0

Respondents by City Tier

Percentage distribution of respondents across city tiers.



C. Analytical Tools

Data was processed using Python (Pandas, SciPy, scikit-learn). The analytical framework included: Ridge and Lasso Regression for Objective 1 (handling multicollinearity among AI feature predictors); Independent and Paired t-tests for Objective 2; One-Way ANOVA with Tukey post-hoc for Objective 3; Mediation Analysis with Sobel Test for Objective 4; and Pearson Correlation with Multiple Regression for Objective 5.

V. DATA ANALYSIS AND RESULTS

A. Objective 1: AI Personalization and Impulse Purchase Behavior

Ridge Regression ($\alpha = 1.0$) and Lasso Regression were applied with "Temptation to Make Impulse Purchases Due to AI Features" as the dependent variable.

Table 2. Ridge and Lasso Regression Coefficients (N = 77)

Predictor Variable	Ridge β	Lasso β	Pearson r	Sig.
Recommended Section	0.664	0.452	0.822	$p < 0.001$
AI Search (Maya)	0.352	0.229	0.802	$p < 0.001$
Usage Frequency	0.387	0.239	0.766	$p < 0.001$
Loyalty (Platform)	-0.383	0.000	0.734	$p < 0.001$
Model R^2	0.744	0.714	—	$p < 0.001$

The Ridge model explains 74.4% of variance. The "Recommended Section" emerges as the strongest predictor ($\beta = 0.664$, $r = 0.822$). Notably, Lasso Regression shrinks the Loyalty coefficient to zero, confirming its minimal unique contribution to impulse purchase behavior after controlling for AI feature variables.

B. Objective 2: Influencer Trust Comparison

Table 3. Descriptive Statistics and t-Test Results (N = 77)

Test	Construct	Mean	SD	t-stat	Sig.
One-sample vs. $\mu=3$	General Influencer Trust	3.34	1.10	2.705	$p<0.01$
One-sample vs. $\mu=3$	Micro-Influencer Authenticity	3.70	0.99	6.231	$p<0.001$
Paired t-Test	Micro vs. Celebrity	—	—	3.282	$p<0.01$

Micro-influencers ($M = 3.70$) are rated significantly higher than celebrity influencers ($M = 3.34$) on authenticity ($t = 3.282$, $p < 0.01$), confirming a "micro-influencer premium" in Gen Z trust perceptions.

C. Objective 3: AI vs. Human Preference by Product Category

One-way ANOVA revealed significant differences in AI trust across city tiers ($F = 7.985$, $p = 0.0007$). Tier-2 cities exhibited the highest AI trust ($M = 3.79$), followed by Metro cities ($M = 3.14$) and Tier-3 cities ($M = 2.21$). This finding contradicts the assumption that metro consumers are the most AI-receptive, suggesting that Tier-2 cities represent the highest-potential market for AI-first strategies.

D. Objective 4: AI-Influencer Synergy

Table 4. Mediation Analysis Results — Sobel Test (N = 77)

Path	Description	β	p-value
Path a ($X \rightarrow M$)	AI Search $\rightarrow$ AI-Served Influencer Content	0.849	0.000
Path b ($M \rightarrow Y$)	AI-Served Content $\rightarrow$ Platform Loyalty	0.897	0.000
Path c (Total)	AI Search $\rightarrow$ Platform Loyalty (Total)	0.901	0.000
Indirect Effect	Mediated effect	0.761	0.000
Sobel Z	Significance	10.24	0.000

Full mediation is established (Sobel $Z = 10.24$, $p < 0.001$), demonstrating that AI search significantly enhances platform loyalty through the delivery of AI-optimized influencer content. AI amplifies rather than replaces influencer effectiveness.

E. Objective 5: Privacy-Loyalty Trade-off

Willingness to share data shows a moderate positive correlation with platform loyalty ($r = 0.580$, $p < 0.001$), while privacy discomfort has only a weak, non-significant negative relationship ($r = -0.209$, $p = 0.069$). The multiple regression model explains 33.7% of variance in loyalty, with the privacy discomfort coefficient being statistically insignificant ($\beta = 0.009$, ns), indicating that Gen Z consumers tolerate data collection when tangible personalization benefits are received.

VI. RESULT AND DISCUSSION

A. AI as the Primary Driver of Impulse Purchases

Within the S-O-R framework, AI recommendations function as highly effective external stimuli that trigger cognitive-affective states leading to unplanned purchase decisions. The Lasso elimination of Loyalty as a predictor suggests that impulse buying in Gen Z is driven by real-time contextual relevance rather than habitual platform attachment. This has direct implications for Myntra's Maya assistant and Blinkit's Recipe Rover.

B. The Micro-Influencer Authenticity Premium

Consistent with the Theory of Planned Behaviour, micro-influencers serve as relatable subjective norm reference groups. Their higher authenticity ratings suggest that Gen Z perceives them as peers rather than paid promoters, making their endorsements more persuasive than celebrity campaigns at significantly lower cost-per-post.

C. City-Tier Gradient in AI Trust

The finding that Tier-2 consumers exhibit the highest AI trust challenges conventional wisdom and reflects the rapid digital adoption in semi-urban India. Tier-3 consumers' lower AI trust ($M = 2.21$) likely reflects lower digital literacy and greater reliance on community-based trust systems, necessitating vernacular-first AI interfaces and local influencer partnerships.

D. AI as an Influencer Amplifier

The full mediation finding represents the study's most significant theoretical contribution. When Blinkit's algorithm delivers a food influencer's recipe content precisely during a grocery search, the combined stimulus effect substantially exceeds that of either AI recommendations or influencer content alone. This validates the proposed AI-Influencer Hybrid mechanism.

E. The Privacy Paradox in Practice

The insignificance of privacy discomfort on loyalty, despite stated concerns, confirms the Privacy Calculus Theory: Gen Z has accepted data sharing as a necessary trade-off, provided that personalization benefits are tangible and timely. This paradox is most pronounced in the 18–24 age cohort.

VII. SUGGESTIONS AND RECOMMENDATIONS

Five evidence-based recommendations emerge from this research:

- 1) **Invest in AI recommendation engines** as the primary conversion driver, enhancing contextual signals such as session behavior and time-of-day patterns (based on Objective 1, $\beta = 0.664$).
- 2) **Shift influencer budgets from celebrities to micro-influencers** (10K–100K followers), who deliver significantly higher authenticity and trust at lower cost (based on Objective 2, $p < 0.01$).
- 3) **Differentiate AI strategies by city tier**, deploying AI-first experiences in Tier-2 cities while using vernacular influencers to introduce AI features in Tier-3 markets (based on Objective 3, $F = 7.985$).

- 4) **Develop AI-driven influencer content delivery systems** that match category-specific creator content to real-time user intent (based on Objective 4, Sobel $Z = 10.24$).
- 5) **Implement transparent data governance** that emphasizes tangible personalization benefits (e.g., "Based on your preferences, you saved ₹850 this month") to maintain the trust threshold (based on Objective 5)

VIII. CONCLUSION

This study demonstrates that for Gen Z consumers in India, AI-driven personalization and influencer marketing are not competing strategies but complementary forces. AI serves as the foundational infrastructure driving impulse purchases ($r = 0.822$), while micro-influencers provide the authentic human connection that algorithms cannot replicate. The evidence for full mediation confirms that the most effective approach combines both, using AI to optimize the timing and targeting of influencer content. As Indian digital commerce moves toward the projected USD 100 billion opportunity by 2030, success will depend on platforms' ability to integrate algorithmic precision with human authenticity across India's diverse geographic and linguistic landscape.

REFERENCES

- [1] Bain & Company, "How India shops online 2025," Bain & Company and Flipkart, 2025.
- [2] Deloitte India, "The rise of discovery commerce in India," Deloitte Insights, 2024.
- [3] V. Bhutani, "Recipe Rover: AI-driven meal recommendations in quick commerce," unpublished, 2023.
- [4] Meta and Bain & Company, "Influencer marketing in India: Trends and outlook," Industry Report, 2024.
- [5] I. Ajzen, "The theory of planned behavior," *Organizational Behavior and Human Decision Processes*, vol. 50, no. 2, pp. 179–211, 1991.
- [6] D. Gefen, E. Karahanna, and D. W. Straub, "Trust and TAM in online shopping: An integrated model," *MIS Quarterly*, vol. 27, no. 1, pp. 51–90, 2003.
- [7] M. Eisenbeiss, "The effects of personalized advertising on click-through rates," *Journal of Interactive Marketing*, vol. 31, pp. 13–24, 2015.
- [8] K. D. Martin and P. E. Murphy, "The role of data privacy in marketing," *Journal of the Academy of Marketing Science*, vol. 45, no. 2, pp. 135–155, 2017.
- [9] D. Grewal, A. L. Roggeveen, and J. Nordfalt, "The future of retailing," *Journal of Retailing*, vol. 93, no. 1, pp. 1–6, 2017.
- [10] K. Jarek and G. Mazurek, "Marketing and artificial intelligence," *Central European Business Review*, vol. 8, no. 2, pp. 46–55, 2019.
- [11] A. Christopher, "Impulse buying behavior among Gen Z in the post-pandemic era," *Journal of Consumer Marketing*, vol. 39, no. 4, pp. 312–325, 2022.
- [12] S. Saleem and A. Bhandari, "Speed and convenience: Drivers of loyalty in quick commerce," *International Journal of Retail & Distribution Management*, vol. 50, no. 8, pp. 987–1003, 2022.
- [13] A. Shah, M. A. Saleem, and S. Bilal, "AI-driven fashion trend prediction: A case study of Myntra," *Journal of Fashion Technology & Textile Engineering*, vol. 11, no. 3, pp. 45–58, 2023.
- [14] S. Mishra, "AI-influencer hybrids: Effectiveness and consumer perception," *Journal of Digital Marketing*, vol. 14, no. 1, pp. 22–38, 2025.
- [15] M. Gerlich, "Category-specific effects of AI versus human recommendations," *European Journal of Marketing*, vol. 59, no. 2, pp. 401–420, 2025.
- [16] R. Koneti, "Trust in AI: The role of transparency and ethical deployment," *AI & Society*, vol. 40, pp. 115–130, 2025.
- [17] L. K. Chaudhari and P. Udasi, "Digital divide in AI adoption: Metro versus non-metro India," *Indian Journal of Commerce & Management*, vol. 13, no. 1, pp. 78–94, 2026.