Advanced International Journal of Multidisciplinary Research

E-ISSN: 2584-0487
editor@aijmr.com

Volume 4, Issue 6, November-December 2026

CrossRef DOI: 10.62127/aijmr.2026.v04i06.1581

AI-Driven Product Recommendations and Consumer Purchase Behaviour on Myntra: A Descriptive Study of Users in Bengaluru

Dr. Kesavan R[1], Hemanth SR[2], Ms.Mary Magadalane A[3]

[1]Assistant Professor, Indian Academy Degree College Autonomous, (Affiliated to Bangalore North University), Hennur Main Rd, Meganahalli, Kalyan Nagar, Bengaluru, Karnataka 560043
[2]Student of BBA, Indian Academy Degree College Autonomous, (Affiliated to Bangalore North University), Hennur Main Rd, Meganahalli, Kalyan Nagar, Bengaluru, Karnataka 560043
[3]Research Scholar, RDB College of Arts and Science, Papanasam, Thanjavur District, Tamil Nadu, India.

Abstract:
Online fashion retailers increasingly rely on AI-driven recommendations to help shoppers navigate extensive assortments, yet the value of such suggestions depends on more than algorithmic relevance. Consumers also weigh brand credibility, reviews, price, trust and the handling of their personal data. This study describes how Myntra users perceive AI-driven recommendations, focusing on reported purchase behaviour, acceptance, purchase intention, satisfaction and overall shopping experience. A descriptive, cross-sectional survey was administered through a structured questionnaire to 121 Myntra users in Bengaluru, recruited by convenience sampling and analysed with frequencies and percentages; no inferential or causal claims are advanced. Recommendations influenced the purchase decisions of 76.03% of respondents at least sometimes, and 78.51% reported a moderate to very high level of influence. Browsing history and previous purchases were jointly the most influential recommendation types (27.27% each). Brand reputation was the leading acceptance factor (30.58%), whereas privacy concerns were the most frequently reported reason for rejection (27.27%). A total of 58.68% were likely or very likely to purchase products recommended according to their preferences. Satisfaction was reported by 52.07% of respondents, with 40.50% neutral; 63.64% rated their post-recommendation shopping experience as good or excellent, and 91.74% judged AI-supported shopping to be the same as or better than manual searching. Recommendations appear to support product discovery and purchase consideration, but their perceived usefulness rests on relevance, trust and responsible data practice. Because the sample was drawn by convenience, the findings should not be generalised to all Myntra users.

Keywords: AI-driven product recommendations; consumer purchase behaviour; personalisation; purchase intention; customer satisfaction; Myntra

Advanced International Journal of Multidisciplinary Research
E-ISSN: 2584-0487
editor@aijmr.com
Volume 4, Issue 6, November-December 2026
CrossRef DOI: 10.62127/aijmr.2026.v04i06.1581

1. Introduction

A fashion retailer's assortment is at once its main attraction and a source of friction for the shopper. When thousands of items compete for attention, the effort of searching can outweigh the pleasure of browsing. Recommendation systems are designed to shift that balance. By ranking or proposing products on the basis of browsing activity, past purchases, item attributes and the behaviour of comparable shoppers, they aim to shorten search and to surface items a consumer might otherwise never encounter. Whether they succeed is a separate question. A suggestion that mirrors a shopper's needs may be welcomed; one that appears irrelevant, expensive or intrusive is simply passed over.

Earlier research indicates that recommendation agents do shape online decision-making, and that perceived usefulness, trust and recommendation quality govern whether consumers adopt them (Häubl & Trifts, 2000; Senecal & Nantel, 2004; Nilashi et al., 2016). Personalisation, however, cuts both ways. The tailoring that makes a shopping environment feel pertinent may also provoke unease about the data from which it is derived. Fashion sharpens this tension, because taste varies with style, occasion, fit, price and trend.

Myntra offers a pertinent setting for examining these questions, since product discovery and personalisation form part of how its users shop for fashion online. The study adopts the consumer's vantage point. It does not evaluate Myntra's algorithm or draw on platform sales records; it asks instead how a sample of users reports responding to AI-driven product recommendations.

1.1 Research problem and purpose

Recommendation systems are typically built to raise engagement, but engagement is not the same as acceptance. Whether users act on a suggestion turns on whether they find it trustworthy, relevant and useful, and company-level performance claims reveal little about how users reach those judgements or why they sometimes reject what is offered. The study therefore sets out to describe the reported influence of AI-driven recommendations on purchase behaviour among Myntra users, and to identify the factors that accompany acceptance, purchase intention and shopping experience.

1.2 Research objectives

Four objectives guided the inquiry. The first was to examine how AI-driven product recommendations influence consumer purchase behaviour among Myntra users. The second was to identify the factors that shape consumers' acceptance of such recommendations. The third was to examine, at a descriptive level, how personalised recommendations relate to customers' purchase intention. The fourth was to evaluate the perceived effectiveness of AI-based recommendations in improving satisfaction and the shopping experience.

2. Review of Literature

Research on recommender systems draws on information retrieval, consumer psychology and digital commerce. The studies considered here are grouped by the question each addresses: how trust is formed, how personalisation translates into purchase-related responses, and where recommendations may mislead or meet resistance.

Advanced International Journal of Multidisciplinary Research
E-ISSN: 2584-0487
editor@aijmr.com
Volume 4, Issue 6, November-December 2026
CrossRef DOI: 10.62127/aijmr.2026.v04i06.1581

2.1 Trust, transparency and recommendation framing

Trust is the most persistent theme in this literature. Nilashi et al. (2016) examined recommendation quality, transparency and website quality as contributors to trust in recommendation agents and found that accurate suggestions alone do not suffice; the openness of the system and the quality of the surrounding website also count. Aljukhadar et al. (2017) approached the issue from the consumer's side, relating self-construal and trust to reactance against recommender advice, which suggests that trust helps decide whether advice is welcomed or resisted. Whang and Im (2018) compared personalised and non-personalised recommendation claims and their implications for trust and behavioural intentions. Their findings indicate that how a recommendation is framed can alter perceived personalisation and, with it, trust.

2.2 Personalisation, value and purchase intention

A second strand connects personalisation to value, emotion and intention. Pappas et al. (2017) studied personalisation quality, message quality, emotions and perceived benefits in personalised online shopping, and linked perceived value and positive emotional responses to purchase intention. Liu (2022), writing on machine-learning-based personalised recommendation in e-commerce, discussed the factors bearing on purchase willingness, among them price, product quality, recommendation relevance and service quality. Yin et al. (2025) examined how consumers' experiences with AI-personalised recommendations shape their intention to click, a result that underlines how prior encounters condition later engagement.

2.3 Bias, adoption and resistance

The third strand is more cautionary. Xiao and Benbasat (2018) examined biased personalised recommendations and warned that suggestions can steer decisions without necessarily improving their quality. Cabrera-Sánchez et al. (2020), analysing the adoption of online recommendation systems, reported that performance expectations, enjoyment and trust supported use, whereas fear of technology could deter it. Reception also varies across consumers and products. Chinchanachokchai et al. (2021) compared responses to different AI-based recommender approaches and suggested that consumer expertise shapes how users evaluate them, while Xie et al. (2022) found that aversion to AI recommendations differs according to whether a product is judged mainly through search attributes or through personal experience.

2.4 Research gap

Taken together, this literature identifies recommendation quality, trust, transparency, consumer expertise and perceived value as central to how AI-based suggestions are received. Much of it, however, rests on experimental designs, broad e-commerce samples or platforms outside India. The present study contributes a focused descriptive account of consumer responses to recommendations on Myntra among users surveyed in Bengaluru, bringing reported influence, acceptance factors, purchase intention, satisfaction and privacy concerns together within a single questionnaire. Given its sampling method and analytical approach, the study is exploratory and descriptive; it does not test causal relationships.

3. Conceptual Framework

The study works with a deliberately non-causal framework. AI-driven recommendations are treated as the stimulus a shopper encounters. The shopper evaluates that stimulus through perceived relevance, trust,

Advanced International Journal of Multidisciplinary Research
E-ISSN: 2584-0487
editor@aijmr.com
Volume 4, Issue 6, November-December 2026
CrossRef DOI: 10.62127/aijmr.2026.v04i06.1581

brand reputation, reviews, price and privacy concerns. The reported responses comprise the actions taken after viewing a recommendation, willingness to purchase, satisfaction and the overall shopping experience. The framework serves to organise the questionnaire and the interpretation of results; it does not imply that any causal pathway has been statistically tested.

4. Methodology

4.1 Research design

A descriptive, cross-sectional survey recorded respondents' reported experiences at a single point in time. Primary survey data were supplemented by secondary material drawn from academic literature, books and industry or institutional sources.

4.2 Population, sample and sampling

The target population comprised adults who had used Myntra's website or application and had encountered product recommendations. The final sample numbered 121 respondents in Bengaluru, recruited through convenience sampling. A complete sampling frame of Myntra users was unavailable, and the study had to be completed within limited time and resources. Respondents were approached in shopping areas and malls in Bengaluru. Table 1 summarises the design.

Table 1. *Sample and study design*

Item	Description
Research approach	Quantitative, descriptive
Design	Cross-sectional survey
Study area	Bengaluru, India
Sample size	121 Myntra users
Sampling method	Non-probability convenience sampling
Instrument	Structured questionnaire with closed-ended questions
Analysis	Frequency and percentage analysis

4.3 Instrument and data collection

The questionnaire combined respondent-profile items with multiple-choice questions aligned to the four objectives. The profile section covered age, gender, monthly income, frequency of shopping on Myntra and duration of platform use. The remaining questions addressed the influence of recommendations, attention to them, recommendation types, and responses to suggestions, acceptance factors, trust and reasons for rejection, data protection, purchase likelihood, satisfaction and shopping experience. Participation was voluntary, and the questionnaire was circulated through Google Forms.

Advanced International Journal of Multidisciplinary Research
E-ISSN: 2584-0487
editor@aijmr.com
Volume 4, Issue 6, November-December 2026
CrossRef DOI: 10.62127/aijmr.2026.v04i06.1581

4.4 Data analysis

Responses were exported to a spreadsheet and summarised as frequencies and percentages. For each response option, the percentage equals the number of respondents selecting it divided by the total number of respondents (N = 121), multiplied by 100. The analysis is purely descriptive: no hypothesis tests, regression models or causal analyses were carried out.

4.5 Ethical considerations and limitations

Participation was voluntary, and results are reported in aggregate. Several limitations qualify the findings. Convenience sampling in a single city restricts generalisability. Self-reported answers may be affected by recall or response bias. The questionnaire captures perceptions rather than clickstream or sales data, and the recommendation environment itself may change over time. Finally, percentage analysis describes the sample but cannot establish statistical relationships between variables.

5. Results and Interpretation

The results are organised around the respondent profile and the four study objectives. All percentages are based on the survey of 121 respondents. Because the sample was selected by convenience, the figures describe these respondents and should not be read as estimates for the full Myntra customer population.

5.1 Respondent profile

Table 2. *Selected respondent characteristics (N = 121)*

Characteristic	Most represented category	n	%
Age	18–25 years	52	42.98
Gender	Female	73	60.33
Monthly income	₹50,000 and above	41	33.88
Myntra shopping frequency	Once in six months	38	31.40
Duration of Myntra use	Less than six months	32	26.45

The largest age group was 18–25 years (42.98%), and women accounted for 60.33% of respondents. Reported shopping patterns were dominated by buying whenever offers were available (33.06%) and by shopping once in six months (31.40%), and respondents' tenure on the platform ranged from newer to longer-term users. Even so, the sample is visibly weighted toward younger and female respondents, which bears on how far the results can travel.

Advanced International Journal of Multidisciplinary Research
E-ISSN: 2584-0487
editor@aijmr.com
Volume 4, Issue 6, November-December 2026
CrossRef DOI: 10.62127/aijmr.2026.v04i06.1581

5.2 Influence of recommendations on purchase behaviour

Table 3. *Reported influence of AI recommendations on purchase decisions*

Measure	Response	n	%
Frequency of influence	Sometimes	41	33.88
Frequency of influence	Often	32	26.45
Frequency of influence	Always	19	15.70
Most influential type	Browsing history	33	27.27
Most influential type	Previous purchases	33	27.27
Action after viewing	Compare with other products	36	29.75
Extent of influence	Moderate	45	37.19

Recommendations were far from universally decisive, yet for most respondents they entered the decision process. Responses of "sometimes", "often" and "always" together made up 76.03%, and 78.51% placed the extent of influence between moderate and very high. Browsing history and previous purchases tied as the most influential recommendation types (27.27% each). The commonest reaction on seeing a recommendation was to compare the item with alternatives (29.75%), which suggests that consumers use suggestions as an input to evaluation rather than as an instruction to buy.

5.3 Factors affecting acceptance and rejection

Table 4. *Factors affecting acceptance and rejection*

Measure	Response	n	%
Main acceptance factor	Brand reputation	37	30.58
Main acceptance factor	Customer ratings and reviews	28	23.14
Main acceptance factor	Discounts and offers	24	19.83
Feature that builds trust	Recommendations based on previous purchases	40	33.06
Main reason for rejection	Privacy concerns	33	27.27
Importance of data protection	Moderately important or above	99	81.82

Brand reputation was selected most often as the main acceptance factor (30.58%), ahead of customer ratings and reviews (23.14%) and discounts and offers (19.83%). Recommendations based on previous purchases were the feature most often credited with building trust (33.06%). On the other side of the ledger, privacy concerns were the leading reason for rejecting a recommendation (27.27%), and 81.82%

Advanced International Journal of Multidisciplinary Research
E-ISSN: 2584-0487
editor@aijmr.com
Volume 4, Issue 6, November-December 2026
CrossRef DOI: 10.62127/aijmr.2026.v04i06.1581

regarded data protection as at least moderately important. Relevance therefore appears insufficient on its own: respondents also leaned on familiar signals of credibility and paid attention to how their personal information is handled.

5.4 Personalisation and purchase intention

Table 5. *Personalisation and purchase intention*

Measure	Response	n	%
Likelihood of purchase	Likely	45	37.19
Likelihood of purchase	Very likely	26	21.49
Main purchase motivation	Matches my interests	41	33.88
Main purchase motivation	Saves shopping time	36	29.75
Action after recommendation	Compare with similar products	39	32.23
Action after recommendation	Add to cart or wishlist	30	24.79

A combined 58.68% of respondents were likely or very likely to buy a product recommended in line with their preferences (37.19% likely; 21.49% very likely). The two leading motivations were that the product matched their interests (33.88%) and that the recommendation saved shopping time (29.75%). Comparison with similar products nonetheless remained the commonest next step (32.23%), and 24.79% added the item to a cart or wishlist. Purchase intention was positive overall, but it typically coexisted with further evaluation.

5.5 Satisfaction and perceived shopping experience

Table 6. *Satisfaction and perceived shopping experience*

Measure	Response	n	%
Satisfaction	Satisfied or very satisfied	63	52.07
Satisfaction	Neutral	49	40.50
Most reported improvement	Faster product discovery	37	30.58
Most reported benefit	Improved product selection	30	24.79
Compared with manual search	About the same	49	40.50
Compared with manual search	Better	41	33.88

Advanced International Journal of Multidisciplinary Research
E-ISSN: 2584-0487
editor@aijmr.com
Volume 4, Issue 6, November-December 2026
CrossRef DOI: 10.62127/aijmr.2026.v04i06.1581

Measure	Response	n	%
Compared with manual search	Much better	21	17.36
Overall experience	Good or excellent	77	63.64

Just over half of respondents (52.07%) were satisfied or very satisfied with Myntra's AI-driven recommendations, while 40.50% were neutral. Faster product discovery was the improvement reported most often (30.58%), and improved product selection was the benefit chosen most frequently (24.79%). Against manual searching, 91.74% rated AI-supported shopping as about the same or better: 40.50% judged it about the same, 33.88% better and 17.36% much better. Some 63.64% described their overall experience as good or excellent, and 7.44% as poor or very poor. The sizeable neutral share indicates that recommendations may be useful without consistently exceeding what users expect.

6. Discussion

The pattern of results is broadly consistent with earlier work linking the usefulness of recommendations and trust to consumer acceptance. That most respondents reported some influence on their purchases accords with the view that recommendation agents shape online consideration and choice (Häubl & Trifts, 2000; Senecal & Nantel, 2004). The prominence of browsing history and previous purchases fits the logic of personalisation, since shoppers appear to respond most readily to suggestions anchored in their own demonstrated interests.

Brand reputation, reviews and discounts figured prominently among acceptance factors, which indicates that algorithmic suggestions are weighed against familiar retail cues rather than accepted on their own authority. This is understandable: a recommendation does not by itself resolve uncertainty about quality, fit or value. The prevalence of comparison and the relatively small share reporting immediate purchase point the same way. In this sample, recommendations seem to support a wider decision process more often than they replace it.

Privacy is the practical counterweight to personalisation. That 81.82% of respondents considered data protection at least moderately important, and that privacy concerns headed the list of rejection reasons, echoes research placing transparency and trust at the centre of recommender-system adoption (Nilashi et al., 2016; Cabrera-Sánchez et al., 2020). The substantial neutral share in satisfaction likewise points to scope for improvement in relevance, explainability and user control. These patterns are descriptive associations within the sample and must not be read as evidence of causal effects.

7. Implications and Recommendations

Three implications for platform design follow from the findings. The first concerns explanation and control. Brief labels stating why an item is shown, such as "based on your previous order" or "because you viewed similar products", would make the logic of a suggestion visible, and accessible controls for

Advanced International Journal of Multidisciplinary Research
E-ISSN: 2584-0487
editor@aijmr.com
Volume 4, Issue 6, November-December 2026
CrossRef DOI: 10.62127/aijmr.2026.v04i06.1581

editing personalisation preferences, reducing repeated suggestions or flagging an item as irrelevant would give users a measure of authority over what they see.

The second concerns credibility cues and comparison. Because respondents relied on brand reputation, ratings and reviews, and frequently compared products before deciding, recommendation areas should place ratings, review counts, brand information and price cues beside each suggestion, together with comparison features, so that options can be evaluated without unnecessary navigation. Price-aware recommendations and clear filters also merit attention, given that price is among the factors known to bear on willingness to purchase (Liu, 2022).

The third concerns data use and measurement. Previous-purchase information deserves careful handling: it was the strongest trust-building recommendation type, yet it depends on personal data, so its use should be accompanied by clear explanations of data practices and accessible privacy controls. Platforms should also pair engagement measures with customer feedback and periodic satisfaction checks, because clicks alone may not show whether recommendations are trusted or genuinely helpful.

8. Conclusion

This study examined how 121 Myntra users in Bengaluru report responding to AI-driven product recommendations. For a substantial share of respondents, recommendations influenced the shopping process, most notably when they drew on browsing history or previous purchases. Brand reputation, customer ratings and reviews, and discounts featured prominently among acceptance factors, whereas privacy concerns were the most frequently reported reason for rejection. More than half of respondents expressed positive purchase intention toward personalised recommendations, and almost two-thirds rated their overall experience as good or excellent.

Recommendations nevertheless seldom led straight to purchase. Respondents typically compared suggested products, checked reviews or saved items for later consideration. AI-based recommendations are therefore best understood as decision-support features whose value depends on relevance, credibility and the consumer's ability to retain control. For Myntra, the practical priority is less to display more suggestions than to make them useful, explainable and respectful of privacy.

The study is bounded by its convenience sample, single-city focus, self-reported data and descriptive percentage analysis. Future research could draw on larger and more diverse samples, compare user groups, test relationships statistically and, where access permits, combine survey responses with observed browsing or purchase behaviour. Designs of that kind would yield stronger evidence on when, and for whom, AI-driven recommendations are most effective.

REFERENCES:

1. Aljukhadar, M., Trifts, V., & Senecal, S. (2017). Consumer self-construal and trust as determinants of the reactance to a recommender advice. Psychology & Marketing, 34(7), 708–719. https://doi.org/10.1002/mar.21017

Advanced International Journal of Multidisciplinary Research

E-ISSN: 2584-0487
editor@aijmr.com

Volume 4, Issue 6, November-December 2026

CrossRef DOI: 10.62127/aijmr.2026.v04i06.1581

2. Cabrera-Sánchez, J.-P., Ramos-de-Luna, I., Carvajal-Trujillo, E., & Villarejo-Ramos, Á. F. (2020). Online recommendation systems: Factors influencing use in e-commerce. Sustainability, 12(21), 8888. https://doi.org/10.3390/su12218888
3. Chinchanachokchai, S., Thontirawong, P., & Chinchanachokchai, P. (2021). A tale of two recommender systems: The moderating role of consumer expertise on artificial intelligence based product recommendations. Journal of Retailing and Consumer Services, 61, Article 102528. https://doi.org/10.1016/j.jretconser.2021.102528
4. Häubl, G., & Trifts, V. (2000). Consumer decision making in online shopping environments: The effects of interactive decision aids. Marketing Science, 19(1), 4–21.
5. Liu, L. (2022). E-commerce personalized recommendation based on machine learning technology. Mobile Information Systems, 2022, Article 1761579. https://doi.org/10.1155/2022/1761579
6. Nilashi, M., Jannach, D., Ibrahim, O., Esfahani, M. D., & Ahmadi, H. (2016). Recommendation quality, transparency, and website quality for trust-building in recommendation agents. Electronic Commerce Research and Applications, 19, 70–84. https://doi.org/10.1016/j.elerap.2016.09.003
7. Pappas, I. O., Kourouthanassis, P. E., Giannakos, M. N., & Chrissikopoulos, V. (2017). Sense and sensibility in personalized e-commerce: How emotions rebalance the purchase intentions of persuaded customers. Psychology & Marketing, 34(10), 972–985. https://doi.org/10.1002/mar.21036
8. Senecal, S., & Nantel, J. (2004). The influence of online product recommendations on consumers' online choices. Journal of Retailing, 80(2), 159–169.
9. Whang, C., & Im, H. (2018). Does recommendation matter for trusting beliefs and trusting intentions? Focused on different types of recommender system and sponsored recommendation. International Journal of Retail & Distribution Management, 46(10), 963–982. https://doi.org/10.1108/IJRDM-06-2017-0122
10. Xiao, B., & Benbasat, I. (2018). An empirical examination of the influence of biased personalized product recommendations on consumers' decision making outcomes. Decision Support Systems, 110, 46–57. https://doi.org/10.1016/j.dss.2018.03.005
11. Xie, Z., Yu, Y., Zhang, J., & Chen, M. (2022). The searching artificial intelligence: Consumers show less aversion to algorithm-recommended search product. Psychology & Marketing, 39(10), 1902–1919. https://doi.org/10.1002/mar.21706
12. Yin, J., Qiu, X., & Wang, Y. (2025). The impact of AI-personalized recommendations on clicking intentions: Evidence from Chinese e-commerce. Journal of Theoretical and Applied Electronic Commerce Research, 20(1), Article 21. ht*tps://doi.org/10.3390/jtaer20010021*