How Indian Online Shoppers Perceive Personalized Product Recommendations: An Exploratory Look at Online Purchase Intention

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***Abstract*—Personalized product suggestions now appear on almost every shopping app and website a consumer visits, yet not every shopper reacts to them the same way. How a person responds seems to hinge on whether a given suggestion feels relevant to what they actually want, whether it is genuinely useful, whether it looks tailored to them individually, and whether the platform delivering it can be trusted. This exploratory study looks at these four perception dimensions and how each relates to online purchase intention among Indian online shoppers. Data were gathered using a structured Google Forms survey made up of 25 statements rated on a Likert scale together with a short demographic section; 27 usable responses were retained for analysis. Internal consistency was checked with Cronbach's alpha, associations were tested with Pearson correlation, and a multiple regression model was run as an exploratory check on the combined effect of all four predictors. All five measurement scales performed well, returning alpha values between 0.860 and 0.945. Recommendation relevance had the strongest bivariate relationship with purchase intention ($r = 0.772$), with recommendation trust ($r = 0.684$), perceived personalization ($r = 0.670$) and perceived usefulness ($r = 0.654$) following behind. When entered together, the four predictors explained 69.3% of the variance in purchase intention, although recommendation relevance was the lone variable that stayed significant at the 5% level once the others were controlled for. Because the sample is small and was not drawn using probability methods, these results are offered as early-stage evidence rather than conclusions that generalize to the wider population, and the study is intended mainly as a template that later work with a bigger Indian sample can refine.**

***Index Terms*—E-commerce, Indian consumers, personalization, purchase intention, recommendation relevance, trust, usefulness.**

I. INTRODUCTION

The way people shop online has shifted considerably as e-commerce has matured. An Indian shopper today can move between a general marketplace, a fashion app, an electronics retailer, a beauty platform and a social-commerce feed within the same browsing session. This convenience, however, comes with a side effect: an overwhelming number of product choices, which makes it harder for shoppers to narrow down to the handful of options that actually suit them. Recommendation engines were built precisely to ease this burden, surfacing products based on a shopper's browsing history, past orders, search patterns and other behavioural cues.

Whether a recommendation actually works, though, depends on more than the algorithm generating it. Shoppers form their own judgement of the experience. A recommended item might feel useful because it cuts down the effort of searching, relevant because it lines up with something the shopper needs right now, personalized because it seems chosen specifically for them, or trustworthy because the platform has earned the shopper's confidence over time. Any of these perceptions, individually or together, can shape whether a shopper even looks twice at a suggested product and whether that glance turns into an intention to buy.

This paper studies these perceptions within an Indian setting, and rather than lumping personalization together with everything else, it treats recommendation relevance, perceived usefulness, perceived personalization and recommendation trust as four distinct constructs, with online purchase intention as the outcome they are measured against. Given that the underlying dataset holds responses from only 27 participants, the analysis is deliberately framed as exploratory rather than confirmatory.

II. REVIEW OF LITERATURE

A. Recommender Systems and Consumer Choice

An early and often-cited survey by Adomavicius and Tuzhilin [1] traced how recommender-system techniques had developed beyond simple preference-matching methods, framing such systems as a response to the problem of information overload facing online users. Building on that technological grounding, Senecal and Nantel [2] turned attention to how online recommendations actually shape consumer choice, arguing that the information a recommendation carries is worth studying from a behavioural, not just a technical, standpoint.

B. Usefulness and Decision Support

Xiao and Benbasat [3] approached e-commerce recommendation agents as tools for decision support, suggesting that shoppers judge such agents largely by how much they actually help during product search and comparison. That framing underpins how perceived usefulness is treated as a construct in the present study.

C. Personalization

Choi, Lee and Kim [4] studied personalized recommender systems from the standpoint of consumer response rather than system accuracy, pointing out that personalization changes the shopper's experience of the platform, not merely the technical output it produces. Following that logic, the present study defines personalization as how closely a set of suggested products appears matched to an individual shopper's tastes and requirements.

D. Trust and Purchase Intention

A separate strand of research points to trust as a factor that matters once recommendations start influencing actual purchase decisions. Xu, Roy and Niculescu [5] looked at how recommender systems shape behaviour within online shopping environments, while Qian et al. [6] focused on personalized recommendations and buying intention among Taobao users, and Yan and Xu [7] examined recommendation agents on shopping platforms more broadly. Roudposhti et al. [8] went a step further and built trust directly into a model of e-commerce recommendations. Read together, these studies make a reasonable case for studying recommendation characteristics side by side with purchase-related outcomes rather than in isolation.

E. Research Gap

Existing work tends to examine recommendation quality, usefulness, personalization, trust and purchase behaviour as separate strands rather than as parts of one framework. Bringing these four perceptions together into a single, compact instrument built for an Indian audience offers a practical entry point for local field research. This study accordingly tests that combined framework using a small set of genuine responses, without claiming the results speak for the broader population of Indian shoppers.

III. OBJECTIVES

- To examine how Indian online shoppers perceive personalized product recommendations.
- To assess how recommendation relevance relates to purchase intention.
- To assess how perceived usefulness relates to purchase intention.
- To assess how perceived personalization relates to purchase intention.
- To assess how recommendation trust relates to purchase intention.

IV. HYPOTHESES

H1: Recommendation relevance is positively associated with online purchase intention.
H2: Perceived usefulness is positively associated with online purchase intention.
H3: Perceived personalization is positively associated with online purchase intention.
H4: Recommendation trust is positively associated with online purchase intention.
H5: The four recommendation perceptions, taken together, explain variation in online purchase intention.

V. RESEARCH METHODOLOGY

The study follows a quantitative, cross-sectional and exploratory design. Primary data were gathered through a Google Forms survey completed by 27 respondents who reported prior experience shopping online. Each item used a five-point Likert scale running from 1 (Strongly Disagree) to 5 (Strongly Agree). Five statements were written for each of five constructs, as summarized in Table I.

TABLE I CONSTRUCT STRUCTURE OF THE QUESTIONNAIRE

Construct	Items	Code
Recommendation Relevance	5	RR1–RR5
Perceived Usefulness	5	PU1–PU5
Perceived Personalization	5	PP1–PP5
Recommendation Trust	5	TR1–TR5
Online Purchase Intention	5	OPI1–OPI5

Each construct's score was taken as the arithmetic mean of its five items. Internal consistency was checked with Cronbach's alpha, associations with purchase intention were tested using Pearson correlation, and a multiple linear regression was run as an exploratory check on the four predictors together. With only 27 respondents drawn through non-probability sampling, all inferential results are read cautiously rather than as definitive statistical proof.

VI. RESPONDENT PROFILE

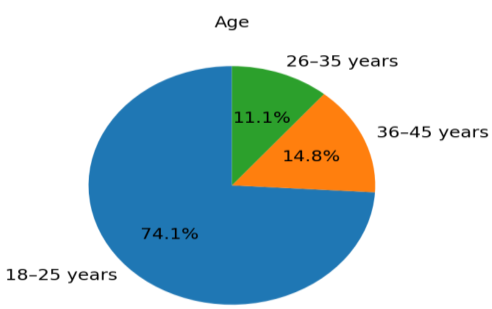

Fig. 1. Age (n = 27)

Age	Freq.	%
18–25 yrs	20	74.1
36–45 yrs	4	14.8
26–35 yrs	3	11.1

Most participants fall in the 18–25 age bracket, which is unsurprising given how the survey link was circulated; the profile is reported here purely for description and should not be read as a stand-in for the wider population of Indian online shoppers.

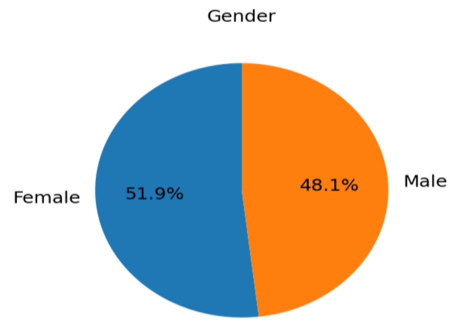

Fig. 2. Gender (n = 27)

Gender	Freq.	%
Female	14	51.9
Male	13	48.1

The gender split among respondents is close to even, though again this reflects only who took the survey rather than the shopper population at large.

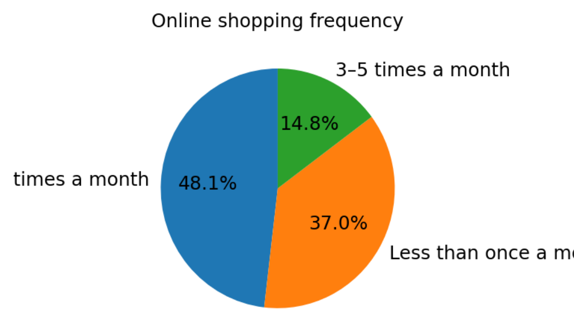

Fig. 3. Online shopping frequency (n = 27)

Frequency	Freq.	%
1–2×/month	13	48.1
<1×/month	10	37.0
3–5×/month	4	14.8

Shopping frequency skews toward occasional rather than heavy use, with under half of respondents ordering more than twice a month.

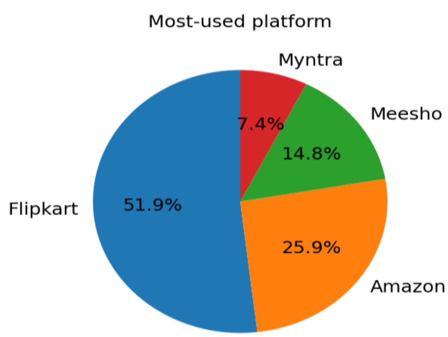

Fig. 4. Most-used platform (n = 27)

Platform	Freq.	%
Flipkart	14	51.9
Amazon	7	25.9
Meesho	4	14.8
Myntra	2	7.4

Flipkart was named most often as the platform respondents use most, followed by Amazon, with Meesho and Myntra trailing behind. As with the other profile figures, this pattern describes the sample only and is not put forward as evidence of platform preference among Indian shoppers generally.

A. Education and Occupation

TABLE IIEDUCATION, OCCUPATION AND SHOPPING PROFILE

Category	Freq.	%
Postgraduate	21	77.8
Undergraduate	5	18.5
Doctorate	1	3.7
Student	19	70.4
Salaried Employee	4	14.8
Professional	3	11.1
Self-employed	1	3.7
Clothing & Fashion	18	66.7
Electronics	4	14.8
Beauty & Personal Care	4	14.8
Home & Kitchen	1	3.7
Rarely (exposure)	8	29.6
Sometimes (exposure)	6	22.2
Often (exposure)	6	22.2
Never (exposure)	5	18.5
Very often (exposure)	2	7.4

VII. RESULTS AND DISCUSSION

TABLE III DESCRIPTIVE STATISTICS AND RELIABILITY

Construct	Mean	SD	α
Recommendation Relevance	3.585	0.830	0.860
Perceived Usefulness	3.511	0.979	0.937
Perceived Personalization	3.674	0.845	0.866
Recommendation Trust	3.585	0.926	0.927
Online Purchase Intention	3.481	1.067	0.945

Every scale cleared an alpha of 0.86, which points to strong internal consistency within this sample. Perceived personalization carried the highest average score (3.674), while purchase intention came in lowest (3.481). Taken together, these figures point to respondents leaning mildly positive overall, though the small sample size means these averages should not be extended beyond the group surveyed.

A. Correlation Analysis

TABLE IV PEARSON CORRELATIONS WITH PURCHASE INTENTION

Predictor	r	p
Recommendation Relevance	0.772	0.0000
Perceived Usefulness	0.654	0.0002
Perceived Personalization	0.670	0.0001
Recommendation Trust	0.684	0.0001

Recommendation relevance stands out with the strongest bivariate link to purchase intention (r = 0.772). Trust, personalization and usefulness each show a meaningful positive relationship as well, pointing toward a pattern where shoppers who see recommendations as more relevant also tend to report a stronger intention to buy. This association is not, on its own, evidence of a causal effect.

B. Exploratory Regression Analysis

TABLE V MULTIPLE REGRESSION RESULTS (DV: OPI)

Predictor	B	β	t	p
Recommendation Relevance	0.902	0.702	3.376	0.003
Perceived Usefulness	0.487	0.447	2.016	0.056
Perceived Personalization	-0.806	-0.638	-1.786	0.088
Recommendation Trust	0.482	0.418	1.835	0.080

The full model returned $R^2 = 0.693$ and an adjusted R^2 of 0.637, with the overall F statistic reaching 12.43 ($p < 0.001$). Of the four predictors, only recommendation relevance held up at the 5% significance level ($B = 0.903$, $p = 0.003$). Perceived usefulness landed just outside conventional significance ($p = 0.056$), while personalization ($p = 0.088$) and trust ($p = 0.080$) fell short of the 5% mark once all four variables were considered jointly. Given that the model rests on just 27 observations and the predictors are conceptually intertwined, these coefficients are best treated as exploratory rather than conclusive.

C. Hypothesis Summary

TABLE VI HYPOTHESIS RESULTS

Hypothesis	Result
H1: Relevance→OPI	Supported
H2: Usefulness→OPI	Not supported at 5%
H3: Personalization→OPI	Not supported at 5%
H4: Trust→OPI	Not supported at 5%
H5: Joint model	Supported; $R^2 = 0.693$

Overall, the results lend early support to recommendation relevance as the standout factor here. The remaining three predictors correlate positively with purchase intention on their own but lose statistical significance once all four are entered into the same regression, which underlines why looking at simple correlations alongside a combined multivariate model tells a fuller story than either would alone.

VIII. FINDINGS

- Respondents' views of personalized recommendations skewed mildly positive overall.
- Among the four predictors, recommendation relevance had the strongest correlation with purchase intention.
- All measurement scales demonstrated strong internal consistency.
- The combined exploratory model accounted for 69.3% of the variation in purchase intention within this sample.
- Recommendation relevance was the only individual predictor that remained statistically significant at the 5% level.

IX. MANAGERIAL IMPLICATIONS

- Platforms should treat matching recommendations to genuine customer needs as a higher priority than simply maximizing relevance scores.
- Recommendation interfaces should aim to cut down search effort rather than flood shoppers with a larger volume of suggested items.
- Personalization efforts should be grounded in real preference signals so that suggestions do not come across as random or repetitive.
- Trust can be built up through accurate product listings, credible seller information, genuine reviews and transparent ratings.
- Indian e-commerce firms would benefit from testing recommendation approaches separately for categories such as fashion, electronics and beauty, rather than applying one strategy uniformly.

X. LIMITATIONS

- The sample is limited to 27 respondents.
- Respondents were reached through non-probability sampling, so the results cannot be generalized to the wider population.
- The study captures purchase intention rather than confirmed purchase behaviour.

- Because the design is cross-sectional, causal claims cannot be made.
- Variables such as privacy concern, perceived intrusiveness, price sensitivity and customer satisfaction are outside the scope of this model.

XI. FUTURE SCOPE

A useful next step would be to repeat this study with a much larger and more varied Indian sample, and to check whether the relationships observed here hold across different age groups, shopping frequencies, product categories and platforms. Incorporating additional variables — privacy concern, perceived intrusiveness, algorithmic transparency, satisfaction and actual purchase behaviour, for instance — could extend the explanatory power of the model. A larger dataset would also open the door to confirmatory factor analysis and more dependable subgroup comparisons than the present sample allows.

XII. CONCLUSION

This study offers early evidence that how Indian consumers perceive personalized product recommendations is tied to their intention to purchase online. Of the four dimensions examined, recommendation relevance shows the clearest connection to purchase intention within this particular sample. Because the sample is small and non-representative, these findings should be read as exploratory groundwork rather than a definitive picture of Indian consumers as a whole. Even so, the questionnaire and the framework built around it give future researchers a workable starting point for a larger empirical study of personalized recommendation systems within India's fast-growing e-commerce landscape.

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APPENDIX: QUESTIONNAIRE

Responses were captured on a five-point scale:
1 = Strongly Disagree,
2 = Disagree,
3 = Neutral,
4 = Agree,
5 = Strongly Agree.

A. Recommendation Relevance
1. Recommended products match my needs.
2. Recommendations suit my current needs.
3. Recommendations match my interests.
4. Suggested products fit my requirements.
5. Recommended products are relevant to me.

B. Perceived Usefulness
1. Recommendations help me find products quickly.
2. Recommendations save my search time.

3. Recommendations help me compare products.
4. Recommendations make shopping easier.
5. Recommendations help me make purchase decisions.

C. Perceived Personalization
1. Recommendations seem selected for me.
2. Platforms understand my preferences.
3. Recommendations reflect my past interests.
4. Recommendations fit my personal needs.
5. Recommendations make shopping more relevant.

D. Recommendation Trust
1. I trust e-commerce recommendations.
2. Recommended products are usually suitable for me.
3. Recommendations from familiar platforms are reliable.
4. I feel confident using recommendations.
5. I am comfortable considering recommended products.

E. Online Purchase Intention
1. I am likely to consider recommended products.
2. Relevant recommendations increase my buying intention.
3. I would consider buying a suitable recommended product.
4. Recommendations can influence my purchase decision.
5. I am likely to buy appropriately recommended products.