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A Study of the Perceived Impact of AI-Driven Personalization on Online Shopping Behaviour among Generation Z in Airoli and Belapur in Navi Mumbai

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Abstract - *This study examines how AI-driven personalization is perceived to relate to online shopping behaviour among Generation Z respondents in Navi Mumbai. The survey was initially intended to focus on Airoli and Belapur, but the response export does not identify respondents' specific localities. A quantitative, cross-sectional survey dataset exported from Google Forms contained 211 timestamped responses. The questionnaire covered online shopping frequency, noticing and usefulness of personalised recommendations, purchases following recommendations, the perceived influence of personalised offers, time-saving, spending beyond original plans, overall influence, and privacy concerns. The analysis uses descriptive frequencies and percentages, alongside exploratory Spearman rank correlations reported for selected ordinal variables. The largest age group was 21–23 years (84; 39.8%), followed by 24–26 years (73; 34.6%). Moderately useful was the most frequent usefulness rating (64; 30.3%). Eighty-three respondents (39.3%) said they had purchased a product because it was recommended, while 79 (37.4%) said they had not and 49 (23.2%) were unsure. Fifty respondents (23.7%) agreed that personalised offers influence buying decisions, and 101 respondents (47.9%) agreed or strongly agreed that recommendations save time. One hundred respondents (47.4%) were somewhat or very concerned about the use of personal data. None of the four reported exploratory correlations reached the .05 significance level. The survey export does not record respondents' specific localities, so differences between Airoli and Belapur cannot be measured. Findings reflect self-reported perceptions, not verified platform algorithms or causal effects. A future survey should record locality, document recruitment, and use consistent response options.*

Keywords: AI-driven personalization; Generation Z; online shopping behaviour; product recommendations; privacy concerns.

INTRODUCTION

Online shopping platforms increasingly use artificial intelligence (AI) to rank products, recommend related items, display personalised offers, and tailor shopping content using browsing or purchase histories. These features may help consumers discover relevant products and reduce search time. They may also influence decisions, encourage purchases that were not initially planned, and raise questions about how personal data are collected and used.

Generation Z frequently interacts with e-commerce applications and personalised digital content, making its reported shopping experiences relevant to the study of AI-enabled retail. However, exposure to a recommendation does not necessarily mean that the recommendation is trusted, useful, or decisive. Consumers may value convenience while remaining uncertain about relevance, price, privacy, and the degree to which recommendations shape their choices.

This study describes survey responses from 211 respondents who reported living in Navi Mumbai. The intended geographical focus is Airoli and Belapur. The supplied response export does not record each respondent's locality, however, so the available data support a Navi Mumbai-level description rather than a valid comparison between

Airoli and Belapur. The study therefore treats its findings as exploratory and descriptive, not as evidence of causal effects.

Objectives

1) To describe respondents' exposure to personalised product recommendations and their perceived usefulness.
2) To examine self-reported purchase behaviour and perceived effects on buying decisions, time-saving, and spending beyond original plans.
3) To assess overall perceived influence of AI-driven personalization and respondents' concerns about personal-data use.
4) To summarise the age, gender, and online-shopping-frequency profile of the respondents.

LITERATURE REVIEW

Bunea et al. (2024) examined Generation Z perceptions of AI in online shopping through an adapted Technology Acceptance Model using 1,128 respondents. Their study connected exposure to, use of, and knowledge about AI with perceived usefulness, ease of use, and purchase intentions [1]. This provides a framework for considering whether personalisation is seen as beneficial by young shoppers.

Singh (2024) examined Generation Z online buying intentions in relation to perceived risk, usefulness, ease of use, privacy, security, and trust [6]. This supports viewing AI personalization as one factor within a broader consumer decision process rather than assuming that recommendations alone determine purchases.

Hu et al. (2025) examined AI-powered personalised product recommendations and spontaneous buying intentions on short-form video platforms. Of 1,043 collected questionnaires, 754 valid responses were analysed; perceived usefulness and trust partially mediated the reported relationship between recommendations and spontaneous buying intention [2]. The platform context differs from general e-commerce, but the study highlights the potential roles of trust and usefulness.

Jayapal (2025) investigated AI-driven personalization and customer loyalty in Indian online shopping, considering privacy concerns as a moderating factor [3]. This is relevant to the present study because a consumer may appreciate relevant recommendations but still worry about the data practices that support them.

Hassan, Abdelraouf, and El-Shihy (2025) studied the relationships among trust, satisfaction, loyalty, and personalised recommendations in AI-driven e-commerce. Their findings suggest that personalised recommendations can affect relationships among these customer outcomes [4]. The present study similarly considers recommendation-related perceptions, although it does not measure loyalty or estimate a structural model.

Ojokoh et al. (2025) reviewed privacy and security issues in recommender systems. Their review discusses how recommendation technologies can improve relevance and engagement while creating risks related to data exposure, misuse, and security breaches [5]. This supports including privacy concerns alongside perceived convenience and influence.

Overall, the literature suggests potential benefits in relevance and convenience, alongside concerns around trust and privacy. The current study adds descriptive survey evidence from respondents in Navi Mumbai. Its results should not be equated with causal estimates from studies using validated measures, experiments, or structural models.

RESEARCH METHODOLOGY

Research design

The study follows a quantitative, cross-sectional, descriptive survey design, with exploratory association analysis for selected ordinal variables. Responses were collected at one point in time, and

the measures represent participants' self-reported experiences and perceptions.

Primary data

Primary data were obtained from a Google Forms questionnaire covering age group, gender, residence in Navi Mumbai, online shopping frequency, platforms and product categories, noticing and usefulness of personalised recommendations, purchases following recommendations, influence of personalised offers, perceived time-saving, extra spending, overall influence, and privacy concerns. The supplied responses export includes respondent names; names are not reproduced in the analysis and should be removed from any shared working dataset.

Secondary data

Secondary data were drawn from six published studies cited in the Literature Review and References [1]–[6]. These sources were used to contextualise AI-based personalization, online purchase intentions, trust, and recommender-system privacy. No separate external numerical dataset was combined with the survey responses.

Sample size

The supplied export contains 211 timestamped response records, which form the reported sample size (N = 211). All 211 entries indicated residence in Navi Mumbai after normalising capitalization variants in the Yes/yes responses. For the spending-beyond-plan item, one response was missing, leaving 210 valid responses for that item.

Sampling method

The supplied export does not document a sampling frame, a list of people invited, or the exact recruitment procedure. The sample is therefore treated as a non-probability convenience sample for reporting purposes, but this classification should be confirmed against the actual fieldwork procedure. Because the number of people invited is not available, a response rate cannot be calculated.

Data analysis and ethical considerations

Categorical responses were summarised using frequencies and percentages. Four exploratory Spearman rank correlations were calculated for selected ordered response variables, using a two-sided significance threshold of .05. Response categories were mapped to ordinal scores; this assumes an order but not equal distances between categories. Correlations do not establish causation. Respondent names in the source export were excluded from the analysis presented here. The supplied export does not include the survey introduction or documentation of consent and ethics review, so these matters cannot be independently verified from the file and should be confirmed with the supervisor. The dataset does not include a specific Airoli/Belapur locality field, limiting geographical conclusions.

OBJECTIVE AND HYPOTHESIS

No.	Objective	Null hypothesis (H0)	Alternative hypothesis (H1)
1	To describe respondents' exposure to personalised product recommendations and their perceived usefulness	$H0_1$: There is no monotonic association between perceived influence of personalised offers and overall perceived influence ($\rho = 0$).	$H1_1$: There is a monotonic association between perceived influence of personalised offers and overall perceived influence ($\rho \neq 0$).
2	To examine self-reported purchase behaviour and perceived effects on buying decisions, time-saving, and spending beyond original plans.	$H0_2$: There is no monotonic association between perceived usefulness of recommendations and overall perceived influence ($\rho = 0$).	$H1_2$: There is a monotonic association between perceived usefulness of recommendations and overall perceived influence ($\rho \neq 0$).
3	To assess overall perceived influence of AI-driven personalization and respondents' concerns about personal-data use..	$H0_3$: There is no monotonic association between perceived time-saving and overall perceived influence ($\rho = 0$).	$H1_3$: There is a monotonic association between perceived time-saving and overall perceived influence ($\rho \neq 0$).
4	To summarise the age, gender, and online-shopping-frequency profile of the respondents	$H0_4$: There is no monotonic association between spending beyond original plans and overall perceived influence ($\rho = 0$).	$H1_4$: There is a monotonic association between spending beyond original plans and overall perceived influence ($\rho \neq 0$).

All four hypotheses are tested using two-sided Spearman rank correlations at a significance level of $\alpha = .05$. Because the response categories are ordinal and the sample is a non-probability convenience sample, the tests are exploratory, and no multiple-testing correction is applied.

Data Analysis and Interpretation

Unless noted otherwise, percentages are calculated using N = 211. The graphs below are Python-generated Matplotlib bar charts based on counts checked against the supplied responses PDF. They show response frequencies rather than causal effects. One response is missing for the extra-spending question, for which valid n = 210.

Respondent profile and online shopping frequency

The largest age group was 21–23 years (84; 39.8%), followed by 24–26 years (73; 34.6%). After normalising the lowercase "male" entry, the gender distribution was 109 male respondents (51.7%), 101 female respondents (47.9%), and one respondent selecting Other (0.5%). Online shopping frequency varied: 55 respondents (26.1%) shopped once a month and 54 (25.6%) selected Rarely. The upper age options overlap conceptually, so future questionnaire versions should use mutually exclusive age bands.

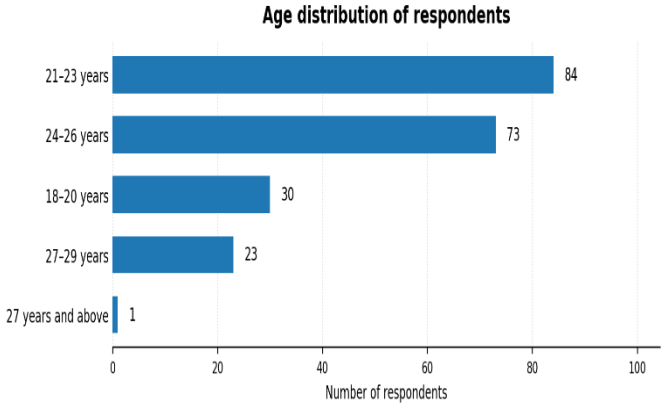


Figure 1. Age distribution of respondents (N = 211).

Note. The survey offered overlapping upper age categories ("27–29 years" and "27 years and above"); the original responses are preserved as recorded.

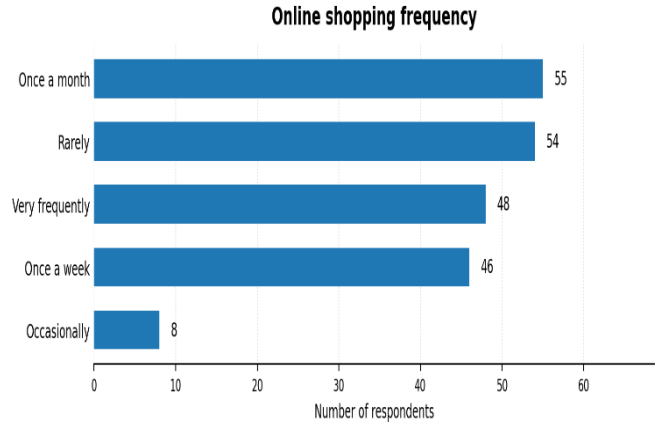


Figure 2. Reported online shopping frequency (N = 211).

Exposure to and usefulness of recommendations

For the item on noticing personalised recommendations, the most frequent recorded response was Sometimes (107; 50.7%). Another 54 respondents (25.6%) selected Yes, 49 (23.2%) selected Rarely, and one (0.5%) selected Never. Because "Yes" is not a frequency category, these figures are reported as recorded response categories rather than interpreted as a valid frequency scale. The item should be revised to use consistent response options in future data collection.

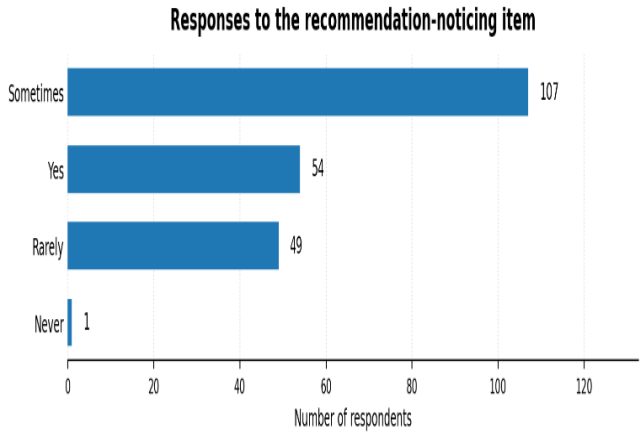


Figure 3. Responses to the item on noticing personalised recommendations (N = 211).

Note. The response option "Yes" is not on the same frequency scale as Sometimes, Rarely, and Never; counts are shown without ordinal interpretation.

Perceived usefulness was mixed. Moderately useful was the most common rating (64; 30.3%), followed by Slightly useful (50; 23.7%) and Not useful (49; 23.2%). Forty-two respondents (19.9%) selected Very useful; five (2.4%) selected Extremely useful, and one (0.5%) selected Not useful at all. These responses do not support a conclusion that recommendations are uniformly useful to all respondents.

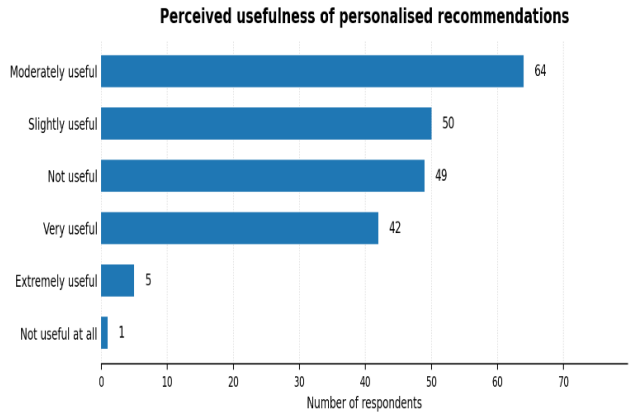


Figure 4. Perceived usefulness of personalised product recommendations (N = 211).

Purchase decisions and personalised offers

Eighty-three respondents (39.3%) reported having purchased a product because it was recommended, 79 (37.4%) said No, and 49 (23.2%) selected Maybe. These are self-reported answers and do not prove that a recommendation caused a purchase.

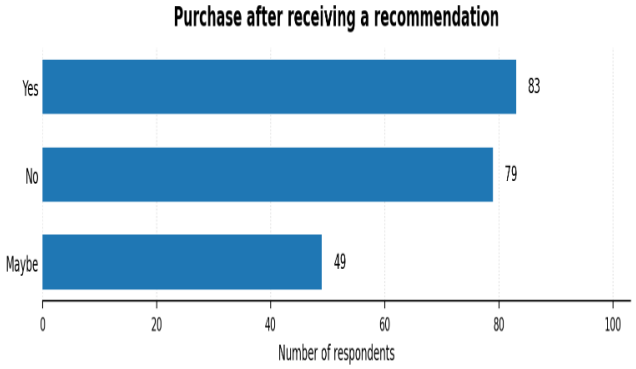


Figure 5. Whether respondents reported purchasing a recommended product (N = 211).

For personalised offers, discounts, and advertisements, 50 respondents (23.7%) agreed and 44 (20.9%) strongly agreed that these influence their buying decisions. Forty-one (19.4%) were neutral, 44 (20.9%) disagreed, and 32 (15.2%) strongly disagreed. The distribution indicates both perceived influence and resistance.

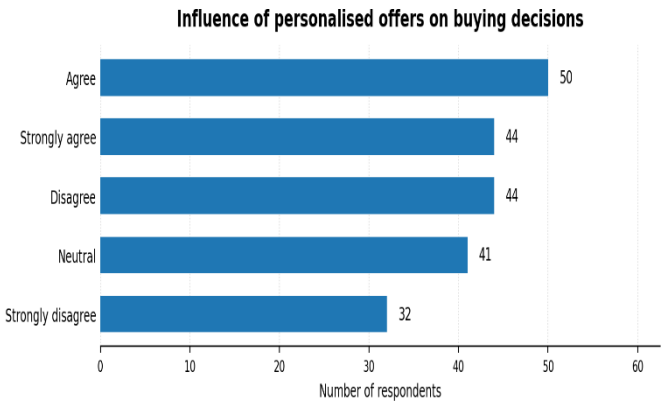


Figure 6. Perceived influence of personalised offers on buying decisions (N = 211).

Time-saving and spending beyond plans

Fifty-one respondents (24.2%) agreed and 50 (23.7%) strongly agreed that personalised recommendations save time. Another 50 (23.7%) were neutral, 33 (15.6%) disagreed, and 27 (12.8%) strongly disagreed. Thus, a substantial group perceived convenience, but the responses were not uniformly positive.

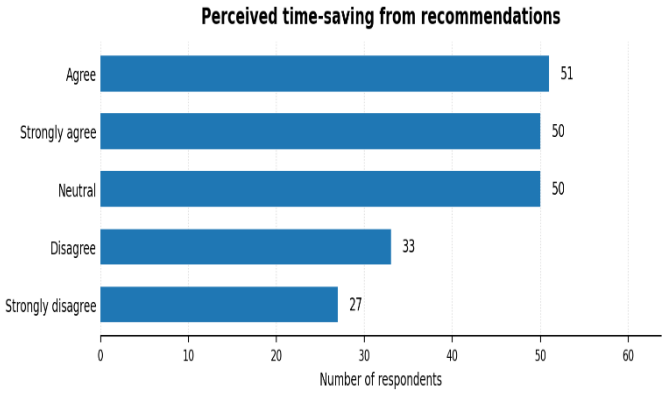


Figure 7. Perceived time-saving from personalised recommendations (N = 211).

For spending beyond original plans, Sometimes was the most common response (56; 26.7% of valid responses), followed by Always (42; 20.0%), Never (41; 19.5%), Often (40; 19.0%), and Rarely (31; 14.8%). One answer was missing, so valid responses for this item total 210. The responses describe self-reported behaviour and cannot independently establish an algorithmic cause.

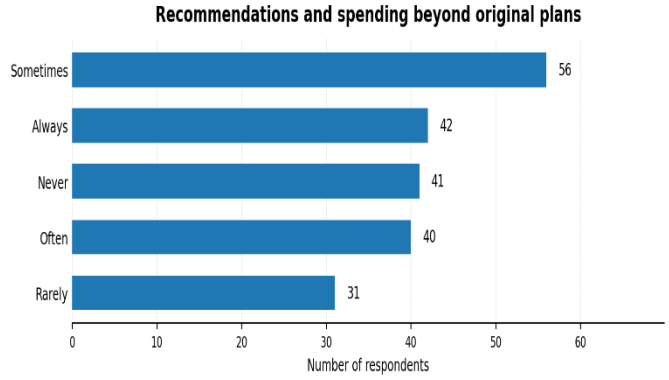


Figure 8. Reported tendency to spend beyond original plans (valid n = 210).

Note. One response was missing; percentages are calculated from the 210 valid answers.

Overall influence and privacy concerns

Overall, 64 respondents (30.3%) reported Moderate influence, 54 (25.6%) High influence, 48 (22.7%) Low influence, 39 (18.5%) No influence, and six (2.8%) Very high influence. Moderate influence was the most common response. The item captures respondents' perceptions, not a measured change in their purchasing behaviour.

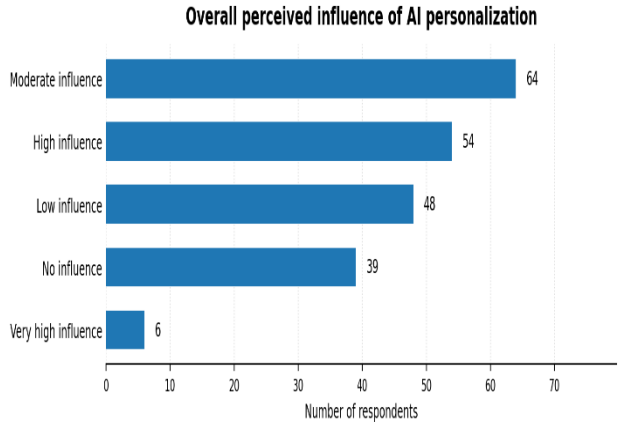


Figure 9. Overall perceived influence of AI-driven personalization (N = 211).

Privacy concerns were also prominent. Fifty-eight respondents (27.5%) were Somewhat concerned and 42 (19.9%) Very concerned, totalling 100 respondents (47.4%). Forty-five (21.3%) were neutral, 34 (16.1%) slightly concerned, and 32 (15.2%) not concerned. The results suggest that data use is an important consideration for many respondents, even where recommendations are perceived as convenient.

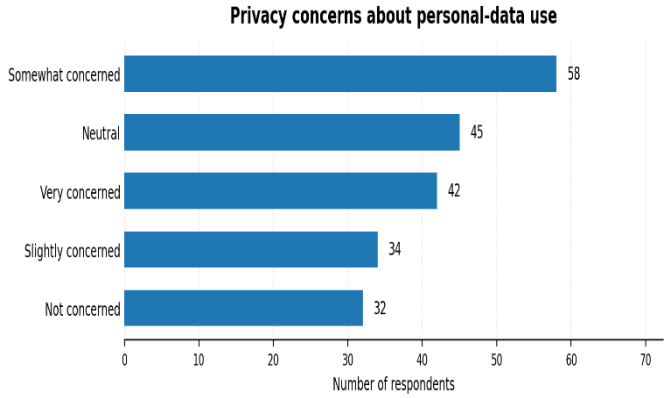


Figure 10. Concern about personal-data use for recommendations (N = 211).

Exploratory association analysis

Table 2. Exploratory Spearman rank correlations

Variables	Spearman ρ	p-value	Decision	Valid n
Offers influence vs. overall influence	0.133	0.053	Not significant at .05	211
Usefulness vs. overall influence	0.107	0.121	Not significant at .05	211
Time-saving vs. overall influence	0.072	0.298	Not significant at .05	211
Extra spending vs. overall influence	0.041	0.554	Not significant at .05	210

None of the four reported correlations reached the .05 significance threshold. The association between agreement that personalised offers influence buying decisions and overall perceived influence was positive but small (ρ = 0.133, p = 0.053), narrowly missing conventional significance. The remaining associations were also small and non-significant. These findings do not demonstrate that personalization has no effect; they indicate that these particular survey measures did not establish statistically significant monotonic relationships in this sample.

Findings

1) The dataset contains 211 timestamped responses; the largest age group was 21–23 years (39.8%).
2) Perceived usefulness of recommendations was mixed, with Moderately useful the most common rating (30.3%).

3) A total of 39.3% reported purchasing a product because it was recommended, while 37.4% said they had not and 23.2% selected Maybe.
4) Respondents reported both potential convenience and influence: 47.9% agreed or strongly agreed that recommendations save time, while views on personalised offers varied.
5) Almost half of respondents (47.4%) were somewhat or very concerned about the use of personal data for recommendations.
6) None of the four reported exploratory Spearman correlations was statistically significant at the .05 level.
7) A comparison between Airoli and Belapur could not be performed because the response export does not identify respondents' specific localities.

LIMITATIONS

1) The study is cross-sectional and based on self-reported answers; it cannot establish causal effects or measure actual platform-algorithm behaviour. The supplied export alone cannot verify that all respondents meet a predefined Generation Z age criterion.
2) The supplied response export does not distinguish Airoli, Belapur, or other Navi Mumbai localities, despite the intended area-specific focus.
3) The sampling frame, invitation count, and exact recruitment procedure are not documented, so representativeness and response rate cannot be established.

CONCLUSION

The survey suggests that AI-driven personalization is visible in respondents' online shopping experiences and is perceived by some as useful, time-saving, and influential in purchase decisions. Nevertheless, usefulness ratings and reported influence are mixed, and a substantial group expresses concern about personal-data use. The exploratory association results did not show statistically significant monotonic relationships between overall perceived influence and the selected perceptions at the .05 level.

The findings should be understood as descriptive evidence about the 211 survey responses, not as proof that AI recommendations cause purchases or extra spending. Because specific locality was not collected, the study cannot support a comparison between Airoli and Belapur. A stronger follow-up study should record locality with suitable privacy safeguards, document recruitment and consent, use consistent non-overlapping response options, and apply validated measures for usefulness, trust, privacy concern, and purchase behaviour.

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