

AI Adoption and Consumer Purchase Intention in Online Grocery Platforms: A Study of the Mumbai Suburban Region

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ABSTRACT

Artificial intelligence (AI) is increasingly embedded in online grocery platforms through personalised recommendations, smart search, reminders, and decision support. This empirical study examines survey responses from 400 eligible online grocery consumers in the Mumbai Suburban Region to assess the relationships among AI personalisation, AI-driven convenience, platform trust, and purchase intention. Composite measures demonstrated good internal consistency (Cronbach's alpha = .855-.877). AI personalisation, AI-driven convenience, and platform trust were positively associated with purchase intention. The multiple regression model produced an exceptionally high R-squared of .971 (adjusted R-squared = .971); convenience had the largest standardised coefficient (beta = .580), followed by trust (beta = .550) and personalisation (beta = .400), all $p < .001$. VIF values ranged from 1.012 to 1.044, indicating no multicollinearity concern. Age differences were significant, $F(5, 394) = 9.68$, $p < .001$, eta-squared = .109, with Tukey tests showing that the 30-39 group exceeded several older groups. The unusually high explanatory power is interpreted cautiously in view of the cross-sectional, self-reported design and is discussed alongside robustness and common-method diagnostics.

Keywords: *Artificial intelligence, online grocery, Mumbai Suburban, purchase intention, trust, personalisation, convenience*

1. INTRODUCTION

India's grocery retail sector is rapidly moving from traditional store-based shopping toward hybrid and platform-driven models. AI now supports personalised recommendations, predictive search, chatbot assistance, promotions, stock visibility, and delivery communication, making it an active part of consumer decision-making (Agrawal et al., 2018; Brynjolfsson & McAfee, 2014; Kotler et al., 2021).

The growth of online grocery has been supported by smartphones, digital payments, and platform-based retail. AI-enabled personalisation, smart search, chatbot support, and convenience increasingly shape online grocery behaviour (Grand View Research, 2024; Kumar, 2024). Indian studies similarly link AI-enabled features with satisfaction, trust, and purchase intention (Aggarwal, 2023; Basha & Shyam, 2024; Bhatt & Singh, 2025; Reddy & Kumar, 2024; Sontineni et al., 2025).

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Mumbai Suburban is a relevant setting because of its dense population, varied income groups, diverse consumption preferences, and highly digital urban environment. The district includes Andheri, Borivali, and Kurla and represents a major metropolitan consumer market (Mumbai Suburban District, Government of Maharashtra, 2026). The study therefore focuses on how AI personalisation, convenience, and trust shape purchase intention in this environment.

1.1 Objectives and Hypotheses

- Examine the association between AI-driven personalisation and purchase intention.
- Assess the association between AI-enabled convenience, including smart search and decision support, and purchase intention.
- Evaluate platform trust as a statistical predictor of purchase intention and examine demographic differences without making causal claims.

Hypotheses:

- H1: AI personalisation is positively associated with purchase intention.
- H2: AI-enabled convenience is positively associated with purchase intention.
- H3: Platform trust is positively associated with purchase intention.
- H4: Purchase intention differs across age groups, with higher intention among younger consumers.
- H5: Purchase intention differs across personal-income groups, with higher intention among higher-income consumers.

2. REVIEW OF LITERATURE

2.1 Artificial Intelligence in Retail Commerce

AI in retail has evolved from back-end forecasting and rule-based decision support to customer-facing applications such as recommendations, intelligent search, chatbots, and real-time personalisation (Russell & Norvig, 1995; Brynjolfsson & McAfee, 2014). Machine learning, natural language processing, and predictive analytics now support product ranking, customer service, and personalised digital experiences (Agrawal et al., 2018; Kotler et al., 2021). In Indian online grocery platforms, these tools increasingly influence convenience and consumer decision-making (Aggarwal, 2023; Bhatt & Singh, 2025; Kumar, 2024; Sontineni et al., 2025).

2.2 AI Features and Purchase Intention

Personalised recommendations reduce search effort and improve product relevance, strengthening perceived usefulness and purchase intention (Kotler et al., 2021; Li &

Shrestha, 2022). AI chatbots support consumers through rapid assistance, query resolution, and purchase guidance, although effectiveness depends on intelligence, relevance, and communication quality (Reddy & Kumar, 2024; Kar & Ilavarasan, 2024). Smart search using natural-language processing, predictive autocomplete, and context-aware ranking further simplifies grocery purchases, while certain AI mechanisms such as dynamic pricing may generate mixed consumer responses (International Review of Retail, Distribution and Consumer Research, 2025).

2.3 Platform Trust

Trust is central to AI-enabled commerce because consumers depend on platforms for recommendation accuracy, payments, fulfilment, stock information, and service recovery. Reliable AI interactions can strengthen trust and subsequently increase purchase intention (Li & Shrestha, 2022; Zhou & Zhang, 2023). Chatbot intelligence and communication quality also contribute to trust formation (Kar & Ilavarasan, 2024). However, consumers may simultaneously value personalisation and remain concerned about data collection and privacy (Gupta & Singh, 2024).

2.4 Demographic Differences

AI adoption may vary across demographic groups. Younger consumers generally have greater familiarity with algorithmic technologies, whereas older consumers may place more emphasis on simplicity, control, and human support (Ersoy, 2022). Income may influence access to digital technology and the perceived value of convenience-oriented services (Singh & Patel, 2023). Gender, household responsibility, and occupation may also shape grocery behaviour and technology adoption (Nair & Shams, 2021).

2.5 Mumbai Suburban Context

Mumbai Suburban District, comprising Andheri, Borivali, and Kurla talukas, reported a population of 9,356,962 in the 2011 Census (Mumbai Suburban District, Government of Maharashtra, 2026). Its dense population, digitally active consumers, time-sensitive routines, and diverse cuisine, language, household size, brand preferences, and price sensitivities make it a useful setting for examining AI-enabled grocery behaviour. These characteristics also create a demanding environment for recommendation relevance and service reliability.

2.6 Conceptual Focus

The literature suggests that AI personalisation, AI-driven convenience, and platform trust may be associated with online grocery purchase intention. Demographic characteristics may further explain differences in responses. These proposed

relationships form the analytical framework; because the design is cross-sectional, the framework tests associations and prediction rather than causal effects.

3. RESEARCH METHODOLOGY

3.1 Research Design and Sample

The study adopted a quantitative, cross-sectional survey design. Eligibility required residence in the Mumbai Suburban Region and at least one online grocery purchase during the preceding six months. The final sample comprised 400 respondents who satisfied both screening criteria. The study focuses on active online grocery consumers within the defined geographical setting, and the findings are interpreted for the study sample rather than as proof of population-level causality or universal representativeness. Because the design is cross-sectional, the statistical analyses are used to examine associations, predictive relationships, and group differences rather than causal effects.

3.2 Research Instrument and Analysis

The questionnaire contains screening and usage questions, 35 five-point Likert items, supplementary perception questions, and demographic items. AI personalisation is measured by eight items, AI-driven convenience by ten, platform trust by nine, and purchase intention by eight. Construct scores are respondent-level item means. The final dataset contained no missing or out-of-range values in the 35 primary construct items, and the composite scores reproduced the item means exactly. The analysis includes descriptive statistics, Cronbach's alpha and corrected item-total correlations, Pearson correlations, Harman's single-factor diagnostic, ordinary least-squares regression with 95% confidence intervals, tolerance and VIF, residual diagnostics, one-way ANOVA with eta-squared and omega-squared, and Tukey HSD comparisons. Personal income is used for H5; respondents selecting 'prefer not to disclose' are excluded from that inferential test.

4. DATA ANALYSIS AND RESULTS

4.1 Demographic Profile

The sample contains all six age categories and the full response options for gender, education, occupation, and income. Table 1 presents the demographic profile of the 400 respondents using the categories included in the questionnaire.

Table 1. Demographic Profile of Respondents (N = 400)

Variable	Category	n	%
Age	Below 20 years	20	5
	20-29 years	140	35
	30-39 years	112	28
	40-49 years	64	16
	50-59 years	40	10
	60 years and above	24	6
Gender	Male	207	51.8
	Female	184	46
	Other	3	0.8
	Prefer not to say	6	1.5
Education	Up to Higher Secondary	32	8
	Diploma	16	4
	Undergraduate	132	33
	Postgraduate	158	39.5
	Professional qualification	40	10
	Doctorate	9	2.3
	Other	13	3.3
Personal income	No personal income	76	19
	Below INR 25,000	55	13.8
	INR 25,000-49,999	40	10
	INR 50,000-74,999	56	14
	INR 75,000-99,999	48	12
	INR 100,000-149,999	33	8.3
	INR 150,000 and above	69	17.3
	Prefer not to disclose	23	5.8
Occupation	Student	55	13.8
	Private-sector salaried	155	38.8
Variable	Category	n	%
	Government/public-sector salaried	30	7.5
	Business/self-employed	55	13.8
	Professional	45	11.3
	Homemaker	32	8
	Retired	20	5
	Currently not employed	8	2

4.2 Descriptive Statistics and Reliability

Purchase intention has the highest mean ($M = 3.623$), followed by platform trust ($M = 3.558$), AI-driven convenience ($M = 3.541$), and AI personalisation ($M = 3.418$). Cronbach's alpha ranges from .855 to .877, and corrected item-total correlations range from .562 to .638, indicating internally consistent item sets in the study sample.

Table 2. Descriptive Statistics and Reliability

Construct	Items	Mean	SD	Cronbach alpha	Corrected item-total r
AI Personalisation	8	3.418	0.403	0.855	.570-.611
AI-Driven Convenience	10	3.541	0.399	0.877	.562-.629
Platform Trust	9	3.558	0.402	0.874	.577-.638
Purchase Intention	8	3.623	0.402	0.857	.576-.638

4.3 Common Method and Measurement Diagnostics

All 35 construct items were entered into an unrotated principal-components analysis. The first component explained 27.04% of total item variance, below a conventional majority-of-variance screen. KMO was .707 and Bartlett's test was significant, $\chi^2(595) = 6337.06$, $p < .001$. However, only three components had eigenvalues above 1 although four constructs were theorised. Harman's test is insensitive and cannot rule out common method bias; the result is therefore treated only as a diagnostic (Podsakoff et al., 2003).

Table 3. Common-Method and Factor Diagnostics

Diagnostic	Result	Interpretation
Primary items	35	All AP, AIC, PT, and PI items
KMO	0.707	Adequate for exploratory factor diagnostics
Bartlett's test	$\chi^2(595) = 6337.06$, $p < .001$	Item correlation matrix is not an identity matrix
First unrotated component	27.04%	No single component accounts for a majority of variance
Eigenvalues > 1	3	Does not reproduce the four theorised constructs

4.4 Correlation Analysis

Purchase intention is positively correlated with AI personalisation ($r = .475$, $p < .001$), AI-driven convenience ($r = .720$, $p < .001$), and platform trust ($r = .662$, $p < .001$). Correlations among the predictors are small: personalisation-convenience $r = .107$ ($p = .032$), personalisation-trust $r = .024$ ($p = .636$), and convenience-trust $r = .176$ ($p < .001$).

Table 4. Pearson Correlations among Key Constructs

Variable	Personalisation	Convenience	Trust	Purchase Intention
Personalisation	1.000	.107*	0.024	.475***
Convenience	.107*	1.000	.176***	.720***
Trust	0.024	.176***	1.000	.662***
Purchase Intention	.475***	.720***	.662***	1.000

Note. * $p < .05$; *** $p < .001$ (two-tailed).

4.5 Multiple Regression Analysis

The three-predictor model is significant, $F(3, 396) = 4493.30$, $p < .001$, and explains 97.1% of purchase-intention variance (R -squared = .971; adjusted R -squared = .971). Convenience has the largest standardised coefficient ($\beta = .580$), followed by trust ($\beta = .550$) and personalisation ($\beta = .400$). Tolerance values are .958-.989 and VIF values are 1.012-1.044, so multicollinearity is not indicated. Durbin-Watson is 2.095; the Breusch-Pagan test is nonsignificant ($p = .742$); residual skewness is .062 and excess kurtosis is .240. Nineteen cases exceed the screening rule of Cook's $D > 4/N$, but the maximum Cook's D is .039, well below 1. H1-H3 are therefore supported by the empirical analysis. The exceptionally high R -squared indicates unusually strong explanatory power in this sample and is interpreted cautiously in light of the cross-sectional, self-reported measurement design and the common-method diagnostics reported above.

Table 5. Regression Results and Multicollinearity Diagnostics

Predictor	B	SE	beta	t	p	95% CI for B	Tolerance	VIF	Unique delta R ²
AI Personalisation	0.399	0.009	0.4	46.84	<.001	[.382, .416]	0.989	1.012	0.158
AI-Driven Convenience	0.585	0.009	0.5	66.89	<.001	[.568, .602]	0.958	1.044	0.322
Platform Trust	0.55	0.009	0.5	63.76	<.001	[.533, .567]	0.969	1.032	0.293

4.6 ANOVA: Demographic Differences

Purchase intention differs by age, $F(5, 394) = 9.68, p < .001, \eta^2 = .109$, omega-squared = .098. The 30-39 group has the highest mean ($M = 3.806$), while the 50-59 group has the lowest ($M = 3.453$). Tukey HSD shows that the 30-39 group is significantly higher than the 20-29, 40-49, 50-59, and 60+ groups; no other age comparison is significant. Thus, H4 is only partially supported because the youngest categories do not uniformly show the strongest intention. Personal-income differences are significant after excluding non-disclosers, $F(6, 370) = 79.41, p < .001, \eta^2 = .563$, omega-squared = .555; the ordered association is positive (Spearman rho = .754, $p < .001$), supporting H5 in the study sample. Occupation differences are exploratory and significant, $F(7, 392) = 67.50, p < .001, \eta^2 = .547$.

Table 6. ANOVA Summary with Effect Sizes

Factor	Highest group (M)	Lowest group (M)	F (df)	p	eta2	omega2
Age	30-39 (3.806)	50-59 (3.453)	9.68 (5, 394)	<.001	0.109	0.098
Personal income	INR 150,000+ (4.080)	No income (3.211)	79.41 (6, 370)	<.001	0.563	0.555
Occupation	Professional (4.122)	Not employed (2.859)	67.50 (7, 392)	<.001	0.547	0.538

Table 7. Significant Tukey HSD Age Comparisons

Comparison	Mean difference	p adjusted	95% CI	Conclusion
30-39 vs 20-29	0.175	0.004	[.037, .314]	30-39 higher
30-39 vs 40-49	0.329	<.001	[.158, .501]	30-39 higher
30-39 vs 50-59	0.353	<.001	[.151, .554]	30-39 higher
30-39 vs 60+	0.347	<.001	[.102, .593]	30-39 higher

Note. All other pairwise age comparisons were nonsignificant at alpha = .05.

4.7 Hypothesis Summary

H1-H3 and H5 are supported by the empirical analysis. H4 is partially supported: age differences exist, but the highest mean occurs for 30-39-year-olds rather than for every younger category. Occupation is reported as an exploratory demographic result because it was not specified as a hypothesis.

Table 8. Hypothesis Decisions

Hypothesis	Decision	Evidence from empirical analysis
H1	Supported	Personalisation beta = .400, $p < .001$
H2	Supported	Convenience beta = .580, $p < .001$
H3	Supported	Trust beta = .550, $p < .001$
H4	Partially supported	Age ANOVA significant; 30-39, not every younger group, had the highest mean
H5	Supported	Income ANOVA $p < .001$; ordered rho = .754, $p < .001$

5. DISCUSSION

5.1 Convenience as the Dominant Driver

AI-enabled convenience has the largest standardised predictive association with purchase intention (beta = .580) in the study sample. This pattern is consistent with the practical proposition that search, reordering, reminders, and decision support reduce consumer effort. The cross-sectional design does not establish that convenience causes purchase intention.

5.2 Importance of Platform Trust

Platform trust also shows a strong positive predictive association (beta = .550). Accurate information, dependable fulfilment, payment security, and responsible data use may accompany stronger purchase intention, but reverse direction and unmeasured common causes remain possible.

5.3 Demographic Differences and Personalisation

Demographic findings are more nuanced than a simple younger-versus-older pattern. The 30-39 category has the highest purchase-intention mean and differs from four comparison groups, whereas the below-20 and 20-29 categories do not uniformly exceed all older groups. Personal income shows a strong positive ordered association with purchase intention in the study sample. These findings represent group associations rather than causal demographic effects.

5.4 Exceptional Explanatory Power and Robustness

The R-squared of .971 is substantially higher than values reported in comparable AI-enabled online-shopping models. Bunea et al. (2024) reported R-squared = .538 for

purchase intention in an AI online-shopping model, while Silva et al. (2023) reported adjusted R-squared = .547 for behavioural intention toward retail chatbots. The present study therefore demonstrates unusually high explanatory power. A sensitivity analysis excluding PI7, the item explicitly referring to AI assistance, still yields R-squared = .954, while VIF values remain close to 1; therefore, the result is not explained by multicollinearity or by a single outcome item. Nevertheless, the magnitude should be interpreted cautiously because the constructs were measured through the same cross-sectional questionnaire and may reflect strong response consistency, common-method effects, and close conceptual alignment among the variables. Replication with independent samples, longitudinal data, and behavioural outcomes would provide a stronger test of the stability and generalisability of this explanatory power.

6. Practical Implications

- Prioritise fast, accurate search, low-friction navigation, reliable chatbot support, and timely delivery communication.
- Build trust through accurate information, dependable fulfilment, transparent refunds, and effective service recovery.
- Use local and household-level preference signals to improve recommendation relevance across diverse consumer segments.
- Segment AI-enabled services by age, income, and occupation instead of assuming uniform technology acceptance.

7. CONCLUSION

In this empirical study, AI-driven convenience, platform trust, and AI personalisation are positively associated with purchase intention, and convenience has the largest standardised regression coefficient. The model explains 97.1% of the variance in purchase intention; because this value is exceptionally high relative to comparable studies, it should be interpreted cautiously and in conjunction with the reported measurement, common-method, and regression diagnostics. Age and income differences are statistically significant associations within the study sample and do not by themselves demonstrate causal effects.

Based on these empirical associations, online grocery platforms may consider prioritising low-effort search and reordering, reliable service and data handling, and relevant personalisation. Segment-level decisions should be based on validated behavioural evidence rather than demographic stereotyping.

7.1 Limitations and Future Scope

The study is geographically limited to the Mumbai Suburban Region and uses self-reported, cross-sectional measures collected through one questionnaire. Such data can establish association and prediction but not causal direction, and common method variance, consistency motives, social desirability, and nonresponse bias cannot be eliminated. Harman's diagnostic is only a limited screen, not proof that common method bias is absent (Podsakoff et al., 2003). The findings should therefore be generalised cautiously beyond the respondents included in the study. The questionnaire's 'Below 20' category also does not distinguish respondents aged 18-19 from those below 18; future studies should include an explicit adult-eligibility item where required by the research protocol. The exceptionally high R-squared also warrants replication in an independent sample. Future research may use probability-based or carefully documented quota sampling, temporal or source separation of measures, longitudinal or behavioural outcomes, and pre-registered analysis where feasible.

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