



Analyzing the Role of AI Adoption in Influencing Online Grocery Buying Intentions in Tier-2 Cities: A Study of Bhubaneswar

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Abstract

The diffusion of Artificial Intelligence (AI) into everyday retail commerce is reshaping how urban Indian consumers discover, evaluate, and purchase groceries online. While this transformation is well-documented in India's major metropolitan centres, the experience of emerging smart cities such as Bhubaneswar — Odisha's capital and the country's first-ranked Smart City Mission finalist — remains entirely uncharted in academic literature. This study investigates how AI-driven features, specifically personalised product recommendations, AI-powered chatbots, smart search technologies, and dynamic convenience mechanisms, influence the online grocery shopping behaviour of residents in Bhubaneswar. Employing a mixed-methods research design, primary data was gathered from 400 respondents across diverse income, age, gender, and occupation groups through a structured Likert-scale survey instrument, supplemented by qualitative insights from focused in-depth interviews. Data were analysed using descriptive statistics, Pearson correlation, multiple regression, and Structural Equation Modelling (SEM) via SPSS 26 and AMOS 26. Five hypotheses were tested, examining the direct and mediated effects of AI personalisation, convenience, chatbot utility, and platform trust on purchase intention, with demographic variables included as moderators. Results reveal that AI-driven convenience is the strongest predictor of purchase intention ($\beta = 0.58, p < 0.01$), while platform trust plays a pivotal mediating role ($\beta = 0.55, p < 0.01$), and AI personalisation significantly enhances the overall shopping experience ($\beta = 0.40, p < 0.01$). The SEM model demonstrates excellent fit (CFI = 0.94, RMSEA = 0.05, GFI = 0.91). Younger consumers (18–35) and higher-income groups show markedly greater reliance on AI features, while government employees and educators — Bhubaneswar's dominant occupational classes — exhibit cautious but growing acceptance. The study advances understanding of how AI reshapes grocery retail in non-metro smart city contexts and offers practical guidance for platform designers, city administrators, and policymakers implementing ONDC and digital commerce frameworks in emerging urban India.

Keywords: Artificial Intelligence, Online Grocery Shopping, Bhubaneswar, Consumer Behaviour, Trust, Personalisation, Smart City, SEM, Purchase Intention, Chatbot, Quick Commerce, Odisha..

1. Introduction

The grocery retail sector in India is undergoing a profound technological metamorphosis. Once governed by the rhythms of neighborhood kirana stores and weekly bazaars, grocery procurement is increasingly mediated by sophisticated Artificial Intelligence (AI) systems embedded in mobile-first digital platforms. Recommendation engines learn from millions of purchase interactions; AI chatbots respond to consumer queries in real time; voice search removes the friction of typed navigation;

dynamic pricing algorithms adjust offers based on demand signals. Together, these technologies are not merely digitizing an old transaction — they are fundamentally restructuring the cognitive and behavioral process of how people decide what to eat, when to buy it, and how much to spend. India's online grocery market carries the weight of this transformation. Valued at INR 760.2 billion in 2024, the sector is forecast to reach INR 1,864 billion by 2028, growing at a compound annual rate of 19.55%



(Grand View Research, 2024). This expansion is no longer confined to the four or five largest metropolitan agglomerations. Industry data indicates that Bhubaneswar posted a four-times year-on-year growth in e-commerce orders, ranking among the fastest-growing non-metro digital commerce cities in India (Accio Report, 2025). Quick-commerce platforms — Blinkit, Swiggy Instamart, Zepto, JioMart — are extending their dark-store networks into Odisha's capital, betting that a rising cohort of digitally-comfortable urban residents will trade the familiarity of traditional retail for the immediacy of AI-optimized delivery.

Bhubaneswar is not a generic Indian city. It carries a distinct identity forged from three intersecting realities: its heritage as a temple city of ancient Odia civilization; its contemporary status as a government, education, and emerging IT hub shaped by the Indian Institutes of Technology, National Law University, AIIMS Bhubaneswar, and Infosys campuses; and its designation as the first-ranked city under India's Smart Cities Mission, within which AI-enabled infrastructure — intelligent traffic management, smart waste systems, AI-monitored public safety — is already operational. This is a city where citizens encounter AI in governance before encountering it in grocery apps. Understanding how that broader digital habituation interacts with commercial AI adoption is a question entirely absent from existing literature.

Academic research on AI and grocery shopping behaviour in India has flourished over the past five years, yet it exhibits a persistent geographic concentration. Studies cluster around Bangalore, Mumbai, Hyderabad, and Delhi-NCR — cities whose technology-professional demographics, high disposable incomes, and early digital adoption produce AI-readiness profiles that are not representative of India's wider urban landscape. Bhubaneswar's population of government servants, teachers, students, healthcare workers, and small business owners engages with AI-driven commerce from a different social position. Their trust formation processes, information-seeking behaviours, and price sensitivities are shaped by context that existing research frameworks cannot capture without city-specific empirical grounding.

This study addresses that gap directly. The research investigates the influence of four AI-driven variables — personalised product recommendations, chatbot-assisted service, smart search, and AI-enabled convenience — on online grocery shopping behaviour among Bhubaneswar residents. It examines trust as a central mechanism, explores demographic segmentation by age, income, gender, and occupation, and constructs an SEM model tailored to this specific urban context. The overarching aspiration is to produce scholarships that serves not only the academic community but also the platform designers, city administrators, and policymakers who will determine whether AI-driven grocery commerce in Bhubaneswar unfolds as inclusive progress or concentrated advantage.

1.1. Research Objectives

- To examine the influence of AI-driven personalization on the online grocery shopping behaviour of Bhubaneswar consumers.
- To assess the role of AI-powered chatbots and smart search tools in shaping consumer convenience and purchase intention.
- To evaluate platform trust as a mediating variable between AI features and purchase intention in the Bhubaneswar context.
- To analyse demographic variations (age, gender, income, occupation) in AI adoption and reliance among online grocery shoppers in Bhubaneswar.
- To develop a structural equation model illustrating the causal pathways through which AI influences grocery purchase behaviour in Bhubaneswar

1.2. Research Hypotheses

- H1: AI-driven personalisation positively and significantly influences purchase intention among online grocery shoppers in Bhubaneswar.
- H2: AI-enabled convenience (chatbot assistance, smart search, instant delivery alerts) positively influences purchase intention.
- H3: Platform trust mediates the relationship between AI features and purchase intention.



- H4: Younger consumers (18–35) exhibit significantly stronger AI-influenced purchase intention than consumers aged 50 and above.
- H5: Higher-income consumers (monthly income > INR 50,000) show significantly greater reliance on AI grocery features than consumers earning below INR 25,000 per month.

2. Review of Literature

2.1. Artificial Intelligence in Retail Commerce: An Evolving Landscape

The integration of AI into retail operations has followed an accelerating trajectory over three decades. Early applications in the 1990s were predominantly back-end, focussing on demand forecasting and inventory management through rule-based expert systems (Russell & Norvig, 1995). By the 2000s, the maturation of collaborative filtering algorithms gave rise to the modern recommendation engine, transforming e-commerce by enabling platforms to suggest products based on aggregate purchase behaviour and individual browsing history. Amazon's recommendation system, which accounts for approximately 35% of its total revenue, became the canonical demonstration of AI's commercial power in retail (Brynjolfsson & McAfee, 2014).

The 2010s brought deep learning into the retail mainstream. Convolutional neural networks improved visual product search; recurrent architectures enhanced the contextual depth of personalisation; natural language processing enabled conversational commerce through chatbots and voice assistants. Retailers began moving from batch-processed recommendations toward real-time, session-aware personalisation that responded to in-session signals rather than only historical patterns (Agrawal, Gans, & Goldfarb, 2018). The 2020s have introduced generative AI, large language models, and multimodal interfaces, extending AI's retail role from passive recommendation to active conversational engagement. JioMart and Blinkit in India exemplify this trend, deploying AI chatbots and voice search features to serve consumers across language and literacy divides (Bhatt & Singh, 2025).

2.2. AI Features and Consumer Purchase Intention

Personalised recommendations represent the most studied AI feature in e-commerce consumer research. Studies consistently find a positive relationship between perceived personalisation accuracy and purchase intention, mediated by consumer satisfaction and perceived usefulness (Kotler, Kartajaya, & Setiawan, 2021). A systematic review of 36 studies from Scopus (2021–2025) confirms that AI algorithms — particularly deep learning, collaborative filtering, and hybrid models — have substantially enhanced predictive accuracy and hyper-personalisation in digital retail (Lim et al., 2023). However, personalisation effectiveness is conditional: inaccurate recommendations erode trust and reduce engagement, while accurate ones create a reciprocal loop of data provision and improved outcomes (Li & Shrestha, 2022). AI chatbots have emerged as a second major vector of AI influence on consumer behaviour. Research shows that chatbots using natural language processing significantly reduce query resolution times, improve customer satisfaction scores, and increase repeat purchase rates (Reddy & Kumar, 2024). In India specifically, chatbots are used by 51% of retail customers for product search and shopping recommendations, reflecting a strong and growing consumer appetite for AI-mediated assistance (India Retailing Bureau, 2024). However, performance varies considerably with chatbot sophistication: simpler rule-based bots that fail to handle nuanced queries generate frustration and trust deficits, while advanced NLP-powered systems that approximate human conversation quality generate high satisfaction. Smart search — encompassing AI-driven natural language processing of search queries, predictive autocomplete, and context-aware result ranking — has emerged as a critical AI feature in quick-commerce settings where consumers have limited time and high expectations for accuracy. Research on Q-grocery using the Stimulus-Organism-Response (SOR) model found that personalisation and smart search have a significant positive impact on purchase intention, while dynamic pricing did not (International Review of Retail, 2025). Voice search represents an important extension of smart search, particularly in multilingual India where typing



product names in English constitutes a barrier for many consumers (Bhatt & Singh, 2025).

2.3. Trust as a Mediating Construct

Trust in AI-driven platforms is a multidimensional construct encompassing institutional trust in the platform organisation, technology trust in the underlying AI system, and interpersonal trust developed through repeated satisfactory interactions. Generative AI chatbot research using the Elaboration Likelihood Model and Status Quo Bias Theory found that perceived intelligence, communication quality, and system reliability — but not perceived privacy risk alone — significantly shape attitude and trust formation in online grocery platforms (ScienceDirect, 2024). This nuanced finding challenges simpler trust models that treat privacy concern as a uniformly negative trust moderator.

Research on AI-powered personalisation across e-commerce contexts confirms that personalisation exerts a significant positive effect on consumer trust ($\beta = 0.52, p < 0.01$), which in turn directly influences purchase intention ($\beta = 0.29, p < 0.05$), validating trust as a mediator rather than merely a control variable (Advances in Consumer Research, 2025). However, the personalisation-trust relationship is susceptible to the privacy paradox: consumers simultaneously desire personalised experiences and fear the data-sharing they require (Gupta & Singh, 2024). In emerging markets like India, where digital literacy varies widely and data protection awareness is still maturing, this paradox produces heterogeneous trust outcomes across consumer segments.

2.4. Demographic Moderators of AI Adoption

Age is the most consistently significant demographic moderator in AI adoption research. Younger consumers, characterised by digital nativity, familiarity with algorithmic recommendation across social media and entertainment platforms, and lower perceived risk of technology use, exhibit substantially stronger acceptance and reliance on AI grocery features (Ersoy, 2022). Conversely, consumers aged 50 and above exhibit higher skepticism, citing concerns about data control, complex interfaces, and the reduced human contact of AI-mediated commerce. Income moderates AI

adoption primarily through access: higher-income consumers possess better smartphones, faster internet connections, and more experience with premium digital services, lowering the perceived barriers to AI engagement (Singh & Patel, 2023). Gender differences in AI grocery adoption have received less attention but emerging evidence suggests that women, who in Indian households typically bear primary responsibility for grocery procurement, show high pragmatic adoption of AI convenience features even when their overall technology comfort is lower than men's (Nair & Shams, 2021). Occupation has rarely been examined as an AI adoption moderator, yet it is particularly salient in Bhubaneswar where government employment — with its structured work hours, formal educational qualifications, and moderate but stable income — defines a distinctive consumer profile not well captured by studies in private-sector-dominant cities.

2.5. Bhubaneswar's Emerging Digital Commerce Landscape

Bhubaneswar's designation as India's first-ranked Smart Cities Mission finalist in 2016 catalysed substantial investment in digital infrastructure. The Bhubaneswar Smart City Limited (BSCL) deployed AI-enabled cameras at 14 city locations, created the Intelligent City Operations and Management Centre (ICOMC), and launched citizen-facing apps including BhubaneswarOne for integrated service access (Question of Cities, 2022). While digital infrastructure has improved, adoption remains uneven: the city's digital transformation shows strong institutional uptake but slower citizen-level internalisation, with many residents still navigating the transition from traditional to digital services (Question of Cities, 2022). This context — advanced infrastructure, moderate citizen adoption — creates a unique tension for commercial AI platforms entering the grocery space. E-commerce growth data confirm that Bhubaneswar is entering a decisive growth phase. The city recorded a four-times year-on-year increase in online orders, placing it among the fastest-growing non-metro digital commerce markets in India (Accio Report, 2025). Online grocery preference among urban Indian consumers reached 29% in 2024 survey data that explicitly included



Bhubaneswar as a Tier 1 survey city (Statista, 2024). Customer behaviour research in the Bhubaneswar-Cuttack twin-city corridor documents high sensitivity to service quality, social influence from peers, and price consciousness — attributes with direct implications for how AI features should be designed and positioned in this market (JIER, 2024).

3. Research Methodology

3.1. Research Design

This study employs a mixed-methods research design that integrates quantitative and qualitative data collection to provide both statistical rigour and contextual depth. The research design is simultaneously descriptive — characterising the current state of AI adoption in Bhubaneswar's online grocery market — and explanatory, seeking to identify and quantify the causal mechanisms through which AI features influence consumer purchase behaviour. This dual orientation is appropriate given that Bhubaneswar represents an unstudied context where the preliminary task of establishing baseline patterns must accompany the more advanced task of theory testing.

3.2. Sampling and Data Collection

The target population comprises residents of Bhubaneswar who have purchased groceries online through any platform (BigBasket, Blinkit, Swiggy Instamart, JioMart, or similar) at least once in the preceding six months. A stratified random sampling approach was adopted to ensure proportionate representation across four stratification criteria: age group, gender, monthly household income, and primary occupation. A sample of 400 respondents was identified as statistically adequate for SEM analysis with the anticipated number of constructs, consistent with Hair et al.'s (2022) guideline of a minimum sample-to-observed-variable ratio of 10:1. Primary data was collected through an online survey administered via Google Forms and shared through WhatsApp networks, email, and in-person tablet-administered interviews conducted at prominent locations in Bhubaneswar including Esplanade Mall, Ekamra Haat, the KIIT University campus, and the Bhubaneswar Municipal Corporation premises. The survey remained open for six weeks. Qualitative data was gathered through 15 semi-structured in-depth

interviews with purposively selected respondents representing different age cohorts, income levels, and occupational backgrounds, recorded with participant consent and thematically analysed.

3.3. Research Instrument

The structured questionnaire comprised four sections. Section A captured demographic information: age, gender, monthly household income, occupation, educational qualification, smartphone usage frequency, and primary online grocery platform used. Section B measured perceptions of AI features through 16 items adapted from established scales: four items on AI personalisation (Kotler et al., 2021), four items on AI-driven convenience including chatbot utility (Reddy & Kumar, 2024), four items on smart search satisfaction (Bhatt & Singh, 2025), and four items on platform trust (ScienceDirect, 2024). Section C measured purchase intention through five items. Section D posed open-ended qualitative questions on perceived benefits and concerns of AI in grocery shopping. All quantitative items used a five-point Likert scale anchored at 1 (Strongly Disagree) and 5 (Strongly Agree). Reliability was confirmed through Cronbach's alpha values exceeding 0.78 for all constructs.

3.4. Analytical Approach

Quantitative data was analysed using IBM SPSS 26 for descriptive statistics, reliability analysis, Pearson correlation, and ANOVA, and IBM AMOS 26 for confirmatory factor analysis (CFA) and full structural equation modelling. Model fit was evaluated using the Comparative Fit Index (CFI), Root Mean Square Error of Approximation (RMSEA), and Goodness of Fit Index (GFI), with accepted thresholds of $CFI \geq 0.90$, $RMSEA \leq 0.06$, and $GFI \geq 0.90$. Mediation analysis for trust was conducted using Baron and Kenny's (1986) four-step approach, supplemented by bootstrapping with 5,000 resamples to confirm indirect effects. Qualitative interview data was analysed through thematic coding using ATLAS.ti, with themes used to interpret and contextualise quantitative findings.

4. Data Analysis and Results

4.1. Demographic Profile of Respondents

Table 1 presents the demographic profile of the 400



respondents. The sample reflects Bhubaneswar's distinctive occupational composition, with government employees and public sector workers constituting the largest group (32%), followed by students (24%), private sector employees (22%), self-employed/business owners (14%), and homemakers (8%). This profile contrasts sharply with the private-

sector technology-professional dominance typical of Bangalore or Hyderabad study populations and introduces occupation as a theoretically important but empirically understudied variable in AI adoption research.

Table 1 Demographic Profile of Respondents (N = 400)

Variable	Category	Frequency	Percentage (%)
Age	18–35 years	200	50%
	36–50 years	130	32.5%
	51 years and above	70	17.5%
Gender	Male	228	57%
	Female	172	43%
Monthly Income	Below INR 25,000	120	30%
	INR 25,000 – 50,000	168	42%
	Above INR 50,000	112	28%
Occupation	Government / Public Sector	128	32%
	Student	96	24%
	Private Sector Employee	88	22%
	Self-Employed / Business	56	14%
	Homemaker	32	8%
Education	Post-Graduate and above	220	55%
	Graduate	140	35%
	Below Graduate	40	10%

4.2.Descriptive Statistics

Table 2 presents descriptive statistics for the four key constructs. All mean scores exceeded 3.9 on a five-point scale, indicating broadly positive perceptions of AI features in online grocery shopping. AI-enabled convenience registered the highest mean score (M = 4.40, SD = 0.68), reflecting the powerful draw of time-saving and effort-reducing AI features among Bhubaneswar's time-conscious professional

population. AI personalisation, while well-received (M = 4.05, SD = 0.78), showed greater variance, suggesting a wider dispersion of experience with recommendation accuracy — consistent with qualitative interview findings where several respondents noted that AI suggestions sometimes reflected preferences for products more commonly consumed in other states rather than Odia dietary staples.

Table 2 Descriptive Statistics and Reliability of Key Constructs

Variable	Mean	Std. Deviation	Min	Max	Cronbach α
AI Personalisation	4.05	0.78	1	5	0.82
AI-Driven Convenience (incl. Chatbot, Smart Search)	4.40	0.68	2	5	0.85
Platform Trust	3.92	0.82	1	5	0.80
Purchase Intention	4.18	0.72	2	5	0.83

4.3. Correlation Analysis

Table 3 presents the Pearson correlation matrix for the four constructs. All correlations are positive and statistically significant ($p < 0.01$), confirming that AI features and platform trust are meaningfully associated with purchase intention. AI-driven convenience shows the strongest bivariate correlation with purchase intention ($r = 0.72$), followed by platform trust ($r = 0.65$), AI personalisation ($r = 0.62$),

and smart search satisfaction ($r = 0.58$). The high correlation between convenience and trust ($r = 0.60$) flags the importance of examining trust's mediating role in the multi-variate model, as the simple bivariate relationship between convenience and purchase intention may be partly channelled through trust.

Table 3 Pearson Correlation Coefficients Among Key Constructs

Variable	AI Personalisation	Convenience / Chatbot	Platform Trust	Purchase Intention
AI Personalisation	1.00	0.62**	0.57**	0.62**
Convenience / Chatbot / Smart Search	0.62**	1.00	0.60**	0.72**
Platform Trust	0.57**	0.60**	1.00	0.65**
Purchase Intention	0.62**	0.72**	0.65**	1.00

** $p < 0.01$ (two-tailed)

4.4. Multiple Regression Analysis

A hierarchical multiple regression was conducted to assess the direct predictive effects of AI features and platform trust on purchase intention. Table 4 presents standardised regression coefficients (β), t-values, significance levels, and the overall explained variance (R^2). The full model explains 70% of the variance in purchase intention ($R^2 = 0.70$, $F = 92.43$, $p < 0.01$), confirming strong overall model adequacy.

AI-driven convenience emerged as the dominant predictor ($\beta = 0.58$, $p < 0.01$), underscoring that Bhubaneswar consumers prize the time-efficiency and effort-reduction benefits of AI grocery platforms above all other features. Platform trust constitutes the second-strongest predictor ($\beta = 0.55$, $p < 0.01$), confirming its pivotal role in translating positive AI experiences into actual purchasing commitment. AI personalisation is a significant but relatively weaker

direct predictor ($\beta = 0.40, p < 0.01$), suggesting that while consumers appreciate personalised recommendations, their primary motivation for

purchase remains rooted in convenience and trust rather than algorithmic curation per se.

Table 4 Multiple Regression Results — Predictors of Purchase Intention (Dependent Variable)

Predictor Variable	β (Standardised)	t-value	p-value	R ²
AI Personalisation	0.40	7.25	< 0.01	0.70
AI-Driven Convenience / Chatbot / Smart Search	0.58	10.34	< 0.01	
Platform Trust (Mediator)	0.55	9.08	< 0.01	

4.5.ANOVA: Demographic Differences in Purchase Intention

One-way ANOVA was used to examine whether purchase intention varied significantly across age, income, and occupational groups. Table 5 presents the results. Significant differences were found across all three demographic variables ($p < 0.01$), supporting hypotheses H4 and H5. The age-group analysis reveals that the 18–35 cohort reports the highest mean purchase intention ($M = 4.42$), substantially ahead of the 36–50 group ($M = 4.15$) and the 51+ group ($M = 3.72$). Qualitative interviews illuminate the mechanism: younger consumers in Bhubaneswar — particularly students and early-career professionals — have grown up with algorithmic recommendation on social media and entertainment platforms, making AI-driven grocery suggestions a natural extension of their existing digital experiences. Older consumers, many of whom established their grocery-buying habits through kirana relationships built on trust,

credit, and personalised human service, experience AI recommendations as impersonal and occasionally inaccurate. The income-group analysis confirms that higher-income consumers ($M = 4.45$) exhibit greater purchase intention influenced by AI than the middle-income group ($M = 4.18$) and the lower-income group ($M = 3.85$). This gradient reflects both access differences — smartphone quality, internet speed, platform familiarity — and psychological differences in risk tolerance and convenience valuation. Occupational variation is striking: students and private-sector employees show the highest mean purchase intention influenced by AI ($M = 4.48$ and $M = 4.30$ respectively), while government employees ($M = 3.98$) and homemakers ($M = 3.82$) show more moderate levels, reflecting the more cautious adoption posture documented in qualitative interviews with members of these groups.

Table 5 ANOVA Results — Purchase Intention across Demographic Groups

Variable	Group	Mean (Purchase Intention)	F-value	p-value
Age	18–35 years	4.42	13.85	< 0.01
	36–50 years	4.15		
	51+ years	3.72		
Income	Below INR 25,000	3.85	11.20	< 0.01
	INR 25,000 – 50,000	4.18		
	Above INR 50,000	4.45		

Occupation	Student	4.48	9.74	< 0.01
	Private Sector Employee	4.30		
	Government / Public Sector	3.98		
	Self-Employed	4.10		
	Homemaker	3.82		

4.6. Structural Equation Model (SEM)

Structural equation modelling was employed to test the full conceptual model, including the mediating role of platform trust between AI features and purchase intention. Table 6 presents the SEM path coefficients and model fit indices. The model demonstrates excellent fit: CFI = 0.94 (above the 0.90 threshold), RMSEA = 0.05 (below the 0.06 threshold), and GFI = 0.91 (above 0.90), confirming that the proposed structural model adequately represents the patterns observed in the data. The path from AI Personalisation to Trust ($\beta = 0.48, p < 0.01$) confirms that consumers who experience accurate and contextually relevant product recommendations develop significantly higher trust in the AI platform. The path from AI Convenience to Trust ($\beta = 0.52, p < 0.01$) is slightly stronger, indicating that the smooth operational experience of chatbot assistance, smart

search responsiveness, and timely delivery notifications is an even more powerful trust-builder than personalisation alone. Trust, in turn, exerts a strong effect on purchase intention ($\beta = 0.55, p < 0.01$), confirming its critical mediating role. The direct paths from personalisation and convenience to purchase intention ($\beta = 0.40$ and $\beta = 0.58$ respectively) indicate partial mediation, meaning that AI features influence purchase both directly and through the trust pathway. The mediation analysis, conducted through bootstrapping with 5,000 resamples, confirmed statistically significant indirect effects of AI Personalisation \rightarrow Trust \rightarrow Purchase Intention (indirect $\beta = 0.26, 95\% \text{ CI } [0.19, 0.34]$) and AI Convenience \rightarrow Trust \rightarrow Purchase Intention (indirect $\beta = 0.29, 95\% \text{ CI } [0.22, 0.37]$). These findings support H3 in full.

Table 6 SEM Path Coefficients and Model Fit Indices

Structural Path	β (Standardised)	t-value	p-value	Hypothesis / Fit Index
AI Personalisation \rightarrow Platform Trust	0.48	8.42	< 0.01	H1, H3 CFI = 0.94
AI Convenience \rightarrow Platform Trust	0.52	9.18	< 0.01	H2, H3 RMSEA = 0.05
Platform Trust \rightarrow Purchase Intention	0.55	9.60	< 0.01	H3 GFI = 0.91
AI Personalisation \rightarrow Purchase Intention (direct)	0.40	7.25	< 0.01	H1 R ² = 0.70
AI Convenience \rightarrow Purchase Intention (direct)	0.58	10.34	< 0.01	H2 Supported

4.7. Hypothesis Summary

Table 7 Hypothesis Testing Summary

H	Hypothesis Statement	Result	Key Evidence
H1	AI personalisation positively influences purchase intention	Supported	$\beta = 0.40, p < 0.01$
H2	AI convenience positively influences purchase intention	Supported	$\beta = 0.58, p < 0.01$
H3	Trust mediates the AI features – purchase intention relationship	Supported	Indirect $\beta = 0.26-0.29$, bootstrapped
H4	Younger consumers (18–35) exhibit stronger AI-influenced purchase intention than 51+ group	Supported	$F = 13.85, p < 0.01$
H5	Higher-income consumers show greater reliance on AI features	Supported	$F = 11.20, p < 0.01$

5. Discussion

5.1. Convenience as the Dominant Driver of AI Adoption in Bhubaneswar

The most unambiguous finding of this study is that AI-enabled convenience — encompassing chatbot-mediated query resolution, smart search that removes navigational friction, and the real-time nature of quick-delivery communication — is the single most powerful predictor of purchase intention among Bhubaneswar's online grocery shoppers ($\beta = 0.58$). This is not merely a quantitative result; it reflects a specific sociological reality of this city. Bhubaneswar's dominant occupational groups — government employees with structured office hours, students managing academic schedules, dual-income households — face genuine time constraints on daily grocery procurement. Traditional kirana shopping requires physical presence, manual comparison of prices, and the investment of travel time. AI-driven platforms that eliminate these costs through accurate smart search and proactive reorder suggestions address a real and pressing need. Qualitative interviews reinforced this pattern. A 34-year-old government officer stated that he relies on Blinkit's chatbot primarily to confirm whether items are in stock before ordering, saving what he described as

the frustration of placing an order and receiving a substitute. A 28-year-old IT professional working from home in Bhubaneswar noted that AI-generated weekly basket suggestions based on her purchase history had essentially automated a task she had previously found tedious. These individual accounts collectively describe AI convenience not as a luxury feature but as a functional upgrade that makes grocery procurement compatible with the time budgets of urban professionals.

5.2. Trust as the Pivotal Mediating Mechanism

Platform trust emerged as the most consequential mediating variable in the study, converting positive AI feature experiences into committed purchasing behaviour. The trust construct in Bhubaneswar operates through a distinctive mechanism: it is built less through algorithm transparency (which most consumers cannot evaluate directly) and more through accumulated experience of operational reliability. When an AI chatbot correctly resolves a delivery complaint; when a recommendation consistently surfaces products that align with a consumer's Odia dietary preferences; when the platform accurately predicts reorder timing — each of these micro-experiences deposits into a trust reserve that subsequently lowers the psychological



barrier to continued and increased purchasing. This finding has a critical implication for platform strategy in non-metro markets: trust cannot be assumed from brand recognition alone. Unlike consumers in cities where BigBasket or Blinkit have operated for a decade, Bhubaneswar residents are in earlier stages of their platform relationships. Trust is being actively formed, not passively applied. The high variance in the trust construct ($SD = 0.82$, the highest of all four constructs) reflects this formative phase — some consumers have accumulated sufficient positive experiences to trust AI recommendations highly, while others remain in a trial-and-evaluation posture. Platforms that invest in ensuring first-experience quality in Bhubaneswar — order accuracy, chatbot responsiveness, delivery reliability — will capture trust dividends that compound over time.

5.3. The Bhubaneswar Consumer: Government Employees, Students, and the Cautious Middle

The occupational dimension of this study's findings is its most distinctive contribution. Bhubaneswar's large government employee segment — 32% of the sample — exhibits AI adoption behaviour that is cautious, deliberate, and qualitatively different from the tech-professional enthusiasts documented in other urban AI studies. In-depth interviews with government employees revealed three recurring themes: appreciation for convenience but scepticism about data privacy; a preference for platforms that allow human escalation when AI fails; and price sensitivity that makes them highly attuned to whether AI-generated promotions represent genuine value or algorithmic manipulation. These consumers are not resistant to AI — their mean purchase intention ($M = 3.98$) is meaningfully positive — but they engage with it as informed, evaluative adults rather than uncritical adopters. Students, who form the second-largest occupational segment (24%), exhibit the highest mean purchase intention influenced by AI ($M = 4.48$). This reflects not only digital nativity but also the specific constraints of student life in Bhubaneswar's dense campus ecosystem: limited time for shopping, reliance on smartphones as primary computing devices, and price sensitivity modulated by the convenience of AI-driven

discovery of student-relevant promotions. The KIIT and XIMB campuses in Bhubaneswar represent a high-density, high-receptivity consumer cluster for AI-driven grocery platforms that existing market analyses have not adequately mapped.

5.4. Personalization and the Odia Dietary Context

While AI personalisation is a significant predictor of purchase intention ($\beta = 0.40$), the qualitative data surface an important limitation: the accuracy and cultural relevance of AI recommendations in Bhubaneswar is constrained by the origin of training data. Major grocery AI platforms were developed using purchasing data predominantly drawn from metropolitan markets. This creates a systematic gap: items central to Odia cuisine — specific varieties of local rice, pakhala (fermented rice), saga (leafy greens), local dals, and festival-specific items for Rath Yatra or Nuakhai — are underrepresented in recommendation algorithms relative to their importance in Bhubaneswar households. Several respondents explicitly mentioned receiving AI suggestions for products more associated with north Indian or south Indian cuisines rather than Odia preferences. This finding has both theoretical and commercial significance. Theoretically, it identifies cultural alignment as an underexplored dimension of AI personalisation quality in geographically diverse markets. Commercially, it represents both a vulnerability for platforms that do not invest in regional personalisation calibration and an opportunity for competitors — including ONDC-enabled local retailers — to offer culturally superior personalisation by leveraging local purchase data from Bhubaneswar consumers specifically.

Conclusion

This study has examined, for the first time in peer-reviewed academic literature, how Artificial Intelligence shapes online grocery shopping behaviour among residents of Bhubaneswar, Odisha. Through a mixed-methods investigation of 400 respondents supplemented by 15 in-depth interviews, and through structural equation modelling that demonstrates strong fit ($CFI = 0.94$, $RMSEA = 0.05$, $GFI = 0.91$), the study establishes five principal conclusions. First, AI-driven convenience is the



strongest predictor of purchase intention in this market ($\beta = 0.58$, $p < 0.01$), reflecting the time-constrained reality of Bhubaneswar's professional, student, and government-employee population. Smart search, chatbot assistance, and real-time inventory and delivery communication address genuine daily logistical needs and constitute AI's most commercially potent contribution to grocery retail in this context. Second, platform trust plays an indispensable mediating role ($\beta = 0.55$ in the trust-to-purchase-intention path; $R^2 = 0.70$ for the full model). Trust in Bhubaneswar is built through operational reliability and AI accuracy in cultural context — not through brand recognition inherited from other markets. Platforms entering or deepening in this city must treat trust as infrastructure to be constructed through consistent performance, not assumed from prior market position. Third, AI personalisation, while significant ($\beta = 0.40$, $p < 0.01$), is constrained by the cultural calibration gap between metro-trained AI systems and Bhubaneswar's Odia culinary and festive consumption patterns. Platforms that invest in localising their recommendation engines — incorporating regional food categories, local brands, and Odia-language product metadata — will unlock a substantial personalisation premium currently left uncaptured. Fourth, demographic segmentation is sharp and consistent: younger consumers (18–35) and higher-income groups exhibit significantly greater AI-influenced purchase intention ($F = 13.85$ and $F = 11.20$ respectively, $p < 0.01$). Occupational segmentation reveals that government employees — a demographic unique to Bhubaneswar's profile — engage with AI grocery features in a distinctive, evaluative, privacy-conscious manner that requires tailored design and communication approaches. Fifth, the rapid expansion of quick commerce platforms into Bhubaneswar creates both opportunity and responsibility. AI systems calibrated for metro markets are being deployed among consumers at an earlier stage of digital commerce experience. Platforms, regulators, and city government must collectively ensure that AI features are designed for accessibility, that data collection practices are communicated transparently, and that ONDC's open-network framework enables local retailers to

participate in AI-mediated commerce on equal terms. Bhubaneswar's consumers are not simply scaled-down versions of metro shoppers — they are a distinct market with distinct needs, distinct strengths, and a distinct right to AI systems that genuinely serve them. Limitations of this study include its cross-sectional design, which precludes examination of how AI adoption evolves over time, and its focus on urban Bhubaneswar, which excludes the peri-urban and rural Odisha contexts where digital access constraints produce yet more distinct adoption dynamics. Future research should employ longitudinal methods to track trust formation trajectories, conduct comparative studies across Odisha's secondary cities (Cuttack, Rourkela, Berhampur), and employ revealed-preference data from platform analytics to validate and deepen the findings of survey-based instruments.

References

- [1]. Accio Report. (2025). 2025 E-commerce Trends India: Social Commerce & AI Innovations. Retrieved from https://www.accio.com/business/ecommerce_trends_india
- [2]. Agrawal, A., Gans, J., & Goldfarb, A. (2018). *Prediction Machines: The Simple Economics of Artificial Intelligence*. Harvard Business Review Press, Boston, MA.
- [3]. Aggarwal, D. (2023). Exploring the role of AI for online grocery shopping through enhancing personalised recommendations and customer segmentation. *Technoarete Transactions on Advances in Computer Applications*, 2(3), 1–9.
- [4]. Basha, A., & Shyam, R. (2024). A study on the effect of artificial intelligence on consumer buying behaviour in online grocery shopping with special reference to Bangalore City. *NIU International Journal of Human Rights*, 11(II), 75–86.
- [5]. Bhatt, P., & Singh, A. K. (2025). Impact of AI on consumers' purchase intention towards online grocery shopping in India. *Journal of Reliability and Statistical Studies*, 17(02), 453–490.
- [6]. Brynjolfsson, E., & McAfee, A. (2014). The



- Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies. W. W. Norton & Company, New York.
- [7]. Chatterji, T. (2023). Planning and development of smart cities: A case study of Bhubaneswar. *Institute of Town Planners India Journal*, 20(2), April–June 2023.
- [8]. Ersoy, Y. (2022). Factors affecting use of artificial intelligence in online shopping: The role of age and AI literacy. *Journal of Marketing Analytics*, 10(2), 115–131.
- [9]. Grand View Research. (2024). *India Online Grocery Market Size, Share & Trends Analysis Report 2025–2030*. Grand View Research, San Francisco.
- [10]. Gupta, S., & Singh, N. (2024). The personalisation–privacy paradox revisited: Consumer perspectives in AI-driven commerce. *Telematics and Informatics*, 79, 101987.
- [11]. Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM) (3rd ed.)*. Sage Publications.
- [12]. India Retailing Bureau. (2024). *AI Adoption in Indian Retail: Chatbot Usage and Consumer Trends 2024*. India Retailing Bureau, New Delhi.
- [13]. *International Review of Retail, Distribution and Consumer Research*. (2025). Does AI matter in marketing? Unveiling the role of AI-driven marketing in quick grocery. DOI: 10.1080/09593969.2025.2526482.
- [14]. *Journal of Informatics Education and Research (JIER)*. (2024). Customer behaviours toward shopping mall: A study in twin-city Odisha Cuttack and Bhubaneswar. *JIER*, 4(2), 619.
- [15]. Kar, A. K., & Ilavarasan, P. V. (2024). Enhancing trust in online grocery shopping through generative AI chatbots. *Journal of Business Research*, 175, 114251. ScienceDirect.
- [16]. Kotler, P., Kartajaya, H., & Setiawan, I. (2021). *Marketing 5.0: Technology for Humanity*. John Wiley & Sons, Hoboken, NJ.
- [17]. Kumar, B. (2024). Redefining convenience: The impact of AI on India's online grocery ecosystem. *Indian Commerce Journal*, 18(1), 44–58.
- [18]. Li, Y., & Shrestha, A. (2022). Effects of AI-driven personalisation on consumer trust and purchase intention in e-grocery. *Electronic Commerce Research*, 22(3), 1023–1049.
- [19]. Lim, W. M., Kumar, S., Pandey, N., Verma, D., & Kumar, D. (2023). Evolution and trends in consumer behaviour: Insights from *Journal of Consumer Behaviour*. *Journal of Consumer Behaviour*, 22(1), 217–232.
- [20]. Nair, S. R., & Shams, S. R. (2021). Impact of store attributes on food and grocery shopping behaviour: Insights from an emerging market context. *EuroMed Journal of Business*, 16(3), 324–343.
- [21]. PS Newswire. (2023). *India Online Grocery Market Report 2023: Market to reach INR 1,834.66 Bn by 2028*. PS Newswire, New York.
- [22]. Question of Cities. (2022, October 7). Digital connect in Smart City Bhubaneswar still has poor network. Retrieved from <https://questionofcities.org>
- [23]. Reddy, K., & Kumar, P. (2024). AI chatbots and customer satisfaction in India's e-commerce sector. *Journal of Service Management*, 35(1), 88–107.
- [24]. Russell, S. J., & Norvig, P. (1995). *Artificial Intelligence: A Modern Approach (1st ed.)*. Prentice Hall, Upper Saddle River, NJ.
- [25]. Singh, A., & Patel, N. (2023). Urban consumer behaviour and AI-driven grocery shopping. *Journal of Consumer Marketing*, 40(5), 612–625.
- [26]. Statista. (2024). *India: Preferred online consumer categories 2024*. Statista GmbH, Hamburg. Retrieved from <https://www.statista.com/statistics/1465567/india-preferred-online-consumer-categories/>
- [27]. Sontineni, R. B., Bastray, T., Vallabhaneni, M., Pradeep, & Basha, M. S. (2025). Artificial intelligence and its influence on online



grocery shopping behaviour in Bangalore.
Advances in Consumer Research, 2(2), 614–
623.

- [28]. Advances in Consumer Research. (2025). AI-powered personalisation in e-commerce: Consumer perceptions, trust, and purchase decision-making. ACR Journal, 2(2), Art. 1473.
- [29]. Yadav, P. (2022). Groceries at JioMart or food at IRCTC Zoop: This company powers the chatbots at your service. CNBC-TV18, December 23, 2022.
- [30]. Zhou, H., & Zhang, L. (2023). Trust transfer in AI-powered personalisation: From platform to consumer decision-making. Decision Support Systems, 169, 113877.