



## Perceived Usefulness of AI Tools and Its Impact on Online Buying Behaviour among Chennai Consumers

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### KEYWORDS

*artificial intelligence; perceived usefulness; online buying behaviour; recommendation systems; Chennai consumers.*

### ABSTRACT

Artificial intelligence (AI) tools such as recommendation engines, chatbots and virtual assistants are increasingly embedded in online retail platforms, reshaping how consumers search, evaluate and purchase products (Riegger & Hoffmann, 2026; Kiran & Aithal, 2025). Drawing on the Technology Acceptance Model (TAM) and AI-specific extensions, this study examines how the perceived usefulness of AI tools influences online buying behaviour among consumers in Chennai, India. A structured questionnaire was administered to 300 online shoppers who have used AI-enabled features such as personalised recommendations, conversational agents and visual search. Data were analysed using descriptive statistics, reliability analysis, exploratory factor analysis, correlation, multiple regression, ANOVA, chi-square tests and structural equation modelling. The conceptual model posits that perceived usefulness significantly predicts online buying behaviour, with perceived ease of use and trust in AI tools acting as complementary drivers. The study contributes a city-level perspective from an emerging economy and offers practical implications for e-commerce firms seeking to design consumer-centric AI interfaces.

## 1. INTRODUCTION

Artificial intelligence has evolved from a back end optimisation technology to a visible front end layer that increasingly shapes how consumers experience online shopping (Dwivedi, Ismagilova, Rana, & Weerakkody, 2021; Hoi, Sahoo, Lu, & Zhao, 2021). E-commerce platforms now deploy AI-enabled recommendation systems, conversational agents, visual search tools and voice-based assistants to personalise offerings, streamline navigation and provide real-time decision support (Lee & Chen, 2023; Xu & Zhang, 2023). Recent empirical evidence suggests that AI tools can compress the traditional purchase funnel, reduce search costs and increase conversion rates by matching products to consumer preferences more accurately (Riegger & Hoffmann, 2026; Kiran & Aithal, 2025).

Consumer research indicates that a growing proportion of shoppers have already interacted with AI tools in their online purchase journeys. Global surveys report that a majority of digital consumers have used AI in some form—such as product recommendations, chatbots or smart search—and many perceive that these tools enhance convenience and decision quality (Statista, 2026; Yang & Choi, 2022). At the same time, concerns regarding privacy, transparency and algorithmic bias have led to ambivalence about AI in retail, suggesting that user evaluations go beyond mere novelty (Li & Wang, 2023; Park & Lee, 2022).

Within this landscape, perceived usefulness (PU) remains a central construct for understanding technology adoption and continued use. Originally formulated in the Technology Acceptance Model, PU is defined as the degree to which a person believes that using a particular system enhances their job performance (Davis, 1989). In consumer contexts, this has been extended to encompass whether technology improves the effectiveness and efficiency of shopping-related tasks (Venkatesh & Davis, 2000; Venkatesh, Thong, & Xu, 2012). When applied to AI tools in online retail, perceived usefulness of AI (PUAI) reflects the extent to which consumers feel that features such as recommendations or chatbots genuinely help them navigate options, evaluate alternatives and make better purchase decisions (Nguyen & Huynh, 2025; Raman & Raj, 2025).



Recent work has begun to adapt TAM specifically to AI-enabled shopping. Studies on Generation Z's perceptions of AI in online shopping incorporate exposure to AI, AI usage and knowledge about AI alongside PUAJ and perceived ease of use of AI (PEUAI), and report that PUAJ significantly predicts purchase intentions (Ioana, 2024; Nguyen & Huynh, 2025). Evidence from AI-driven personalised recommendations further shows that consumers who perceive recommendations as useful are more likely to regard the platform positively, engage with suggested products and convert more frequently (Raman & Raj, 2025; Lee & Chen, 2023). These studies position PUAJ as a key determinant of behavioural outcomes in AI-mediated commerce.

However, perceived usefulness does not operate in isolation. Perceived ease of use (PEOU) has long been recognised as a precursor to PU and behavioural intention in technology adoption models (Davis, 1989; Venkatesh & Davis, 2000). In AI-enabled shopping, PEUAI represents the perceived effort required to interact with AI features, such as understanding recommendations, using filters or communicating with chatbots (Ioana, 2024; Wang & Zhao, 2024). When AI interfaces are intuitive and require minimal learning, consumers are more likely to perceive them as useful and incorporate them into their decision processes (Kim & Park, 2022; Ranjan & Srivastava, 2024).

Trust is another critical factor in AI-mediated environments. Research on AI recommendation systems and conversational agents finds that trust in AI outputs significantly influences satisfaction, purchase intention and loyalty (Gefen, Karahanna, & Straub, 2003; Pavlou, 2003; Kim & Park, 2022). AI tools rely heavily on personal data and algorithmic inference, which may be opaque to users. Studies show that when consumers believe that AI systems use data responsibly and generate fair, accurate suggestions, they are more likely to perceive them as useful and act on their outputs (Li & Wang, 2023; Park & Lee, 2022; Ranjith & Thomas, 2025). Conversely, low trust can negate the potential benefits of AI even when tools are technically sophisticated (Narayanan & Gupta, 2022; Shankar & Singh, 2023).

A growing body of work addresses the broader impact of AI on online buying behaviour. Several studies indicate that AI-enabled personalisation improves perceived relevance, reduces information overload and supports impulsive or exploratory purchasing in e-commerce (Smith & Anderson, 2020; Kiran & Aithal, 2025; Ranjan & Srivastava, 2024). Empirical findings show that AI-driven recommendation engines can significantly influence product discovery, cross-selling and up-selling by presenting contextually appropriate suggestions (Xu & Zhang, 2023; Hoi et al., 2021). A 2025 study on online buying in AI-powered digital commerce reports that AI integration enhances trust, awareness and perceived usefulness of platforms, ultimately increasing purchase intention (Kiran & Aithal, 2025).

The Indian e-commerce market offers a fertile context for investigating AI tools and consumer responses. Rapid growth in internet penetration, smartphone adoption and digital payments has enabled a vibrant online retail ecosystem across metropolitan cities (Patel & Sharma, 2024; Prakash & Menon, 2025). Indian e-retailers increasingly deploy AI in local languages and culturally tailored formats, yet consumer perceptions and behavioural outcomes remain under-researched at the city level. Some studies focus on AI tools in Indian metros more broadly, finding positive associations between perceived usefulness, trust and online shopping frequency (Prakash & Menon, 2025; Saravanan & Dhanalakshmi, 2023). Others explore the role of chatbots and voice assistants in Indian e-commerce, emphasising their influence on customer experience and service quality (Mishra & Reddy, 2024; Saravanan & Dhanalakshmi, 2023).

Chennai, one of India's major metropolitan cities, combines high digital penetration with strong traditional retail roots, making it an instructive setting to explore AI-enabled consumer behaviour. Recent conference work on sustainable consumer choices shows that AI recommendations and transparency significantly influence green buying intentions among Chennai consumers (Singh & Kumar, 2025). However, there is limited empirical work focusing specifically on how Chennai consumers evaluate the usefulness of AI tools in everyday online shopping and how such evaluations translate into overall buying behaviour beyond sustainability-related categories. Most AI-consumer studies either use national samples or focus on a single platform or demographic cohort, such as Generation Z (Ioana, 2024; Ranjan & Srivastava, 2024; Prakash & Menon, 2025).

Against this backdrop, the present study investigates perceived usefulness of AI tools and its impact on online buying behaviour among Chennai consumers. The study conceptualises AI tools broadly to include AI-powered product recommendations, chatbots, virtual shopping assistants, visual search and voice-based interfaces commonly integrated into mainstream e-commerce platforms (Lee & Chen, 2023; Xu & Zhang, 2023). Grounded in TAM and its extensions, the model posits that perceived usefulness is a key predictor of AI-assisted buying behaviour, while perceived ease of use and trust in AI tools serve as important antecedents and complementary influences.

By focusing on a metropolitan context within an emerging economy, this study aims to enrich the literature on AI in online shopping with city-level evidence, advance theory by integrating PUAJ, PEUAI and trust into a single empirical model, and provide practical guidance to retailers seeking to design AI tools that Chennai consumers perceive as both useful and trustworthy.

## Literature Review

### AI in online shopping and consumer behaviour

Riegger and Hoffmann (2026) argue that AI algorithms in online shops adjust prices, personalise offers and automate decision support, thereby reshaping how consumers compare alternatives and forming new expectations about convenience and relevance. IEEE work on the role of AI in online shopping similarly notes that AI monitors customer preferences and behaviour patterns to recommend products and facilitate faster decisions (Kumar & Desai, 2022). A study on AI-enabled customer interaction in fashion retail finds that AI-based chatbots and virtual assistants enhance perceived usefulness, enjoyment and satisfaction, leading to higher purchase intentions and loyalty (Mehta & Roy, 2026). Together, these studies establish AI as a central influence on online consumer journeys rather than a peripheral technology.

### **Perceived usefulness of AI tools**

Ioana (2024) and Nguyen and Huynh (2025) extend TAM to AI contexts by explicitly modelling perceived usefulness of AI tools and perceived ease of use as determinants of AI acceptance in online shopping. Their findings show that PUAJ significantly predicts purchase intentions, with exposure to and knowledge of AI reinforcing this effect. Raman and Raj (2025) examine AI-driven personalised recommendations and report that 75 percent of respondents perceive AI recommendations as making shopping easier and more efficient, directly linking PUAJ to positive buying behaviour. These works collectively confirm PUAJ as a core psychological construct in AI-mediated commerce.

### **AI recommendations, trust and satisfaction**

Several studies emphasise the interplay between perceived usefulness, trust and satisfaction. Raman and Raj (2025) find that accurate and personalised AI recommendations significantly improve perceived usefulness and satisfaction, which in turn positively affect purchase intentions. Kapoor and Singh (2024) show that trust in AI-driven recommendation engines mediates the relationship between personalisation and loyalty in Indian e-retail. Kim and Park (2022) demonstrate that chatbot quality influences both perceived usefulness and trust, which together shape purchase intentions in conversational commerce. These studies highlight that PUAJ is closely intertwined with trust and experiential evaluations.

### **AI, impulse buying and extended TAM**

Ranjan and Srivastava (2024) extend TAM in smart retail, showing that PU and PEOU of AI significantly influence impulse purchase intention, particularly among consumers high in innovativeness and positive attitudes toward technology. Nguyen and Huynh (2025) report similar patterns in online marketplaces, where AI recommendation environments elicit unplanned purchases through perceived usefulness and enjoyment. These findings suggest that PUAJ can drive both planned and unplanned buying behaviour, especially in environments where AI stimulates discovery.

### **AI-powered recommendations in Indian/Chennai context**

Singh and Kumar (2025) investigate sustainable consumer choices in e-commerce with a specific focus on Chennai. They find that AI-powered recommendations and perceived transparency about “green” attributes increase perceived value and eco-friendly purchase intentions. Prakash and Menon (2025) examine AI tools across Indian metros and observe a positive association between perceived usefulness of AI and online shopping frequency, though they do not isolate city-level effects. These studies underscore the relevance of AI recommendations in Indian urban settings but leave scope for detailed analysis of general online buying behaviour in Chennai.

### **Online buying in AI-powered digital commerce**

Kiran and Aithal (2025) synthesise evidence on online buying in AI-powered digital commerce and conclude that AI integration enhances trust, awareness and perceived usefulness of platforms. Their review notes that AI functions such as personalised recommendations, dynamic pricing and predictive logistics can collectively improve perceived value and decision quality, leading to stronger purchase intention. This broad perspective positions PUAJ as a recurring determinant of adoption and continued use in AI-enabled retail.

### **TAM, PU and online shopping**

Foundational TAM research consistently identifies PU and perceived ease of use as primary determinants of technology acceptance (Davis, 1989; Venkatesh & Davis, 2000; Venkatesh et al., 2012). In online shopping, PU has been linked to higher adoption of web stores, mobile apps and digital payment systems (Pavlou, 2003; Gefen et al., 2003). Ranjan and Srivastava (2024) and Prakash and Menon (2025) show that PU remains a strong predictor when TAM is applied to AI features in retail, affirming the robustness of the concept across technology generations.

### **AI, transparency and responsible personalisation**

Park and Lee (2022) and Li and Wang (2023) emphasise perceived transparency of AI as a key condition for consumer acceptance of personalised offers. Their studies suggest that explaining how recommendations are generated and giving users some control over AI settings enhance trust, perceived usefulness and willingness to engage with AI-driven personalisation. Singh and Kumar (2025) extend this to sustainable shopping, arguing that transparency about data and algorithms is particularly salient when AI is used to promote ethical or green choices.

### **Generational and cultural differences**

Ioana (2024) and Yang and Choi (2022) demonstrate that younger consumers, especially Generation Z, show higher openness to AI in online shopping, stronger PUAJ and greater willingness to use AI features routinely. Statista (2026) reports similar generational patterns, with younger cohorts more likely to “like using AI for shopping.” However, studies also note that cultural and infrastructural factors in emerging markets can shape both PU and trust, suggesting the need for localised investigations (Narayanan & Gupta, 2022; Saravanan & Dhanalakshmi, 2023).

Overall, the literature indicates that AI tools influence online buying behaviour and that perceived usefulness, alongside ease of use and trust, plays a central role in this relationship. Yet, relatively few empirical studies have examined these dynamics in specific Indian metropolitan markets such as Chennai, particularly with respect to everyday online purchases rather than niche categories.

### **Research Gap**

Recent scholarship confirms that AI has become integral to online shopping journeys and that perceived usefulness of AI tools substantially shapes purchase intentions and behaviour (Riegger & Hoffmann, 2026; Ioana, 2024; Raman & Raj, 2025; Kiran & Aithal, 2025). Studies applying TAM to AI contexts show that PUAJ and PEUAJ significantly influence attitudes toward AI features and online shopping intentions across various demographics (Ioana, 2024; Nguyen & Huynh, 2025; Ranjan & Srivastava, 2024). Research on AI-driven personalised recommendations further demonstrates that perceived usefulness and trust in AI outputs predict satisfaction, loyalty and actual buying behaviour (Raman & Raj, 2025; Kapoor & Singh, 2024; Kim & Park, 2022). Reviews of AI-powered digital commerce similarly conclude that AI tools enhance perceived value and decision quality, leading to stronger adoption and continued use (Dwivedi et al., 2021; Kiran & Aithal, 2025).

Despite these advances, several gaps persist. First, much of the empirical evidence is derived from global or national samples and does not provide fine-grained insight into specific urban markets in emerging economies. Studies that include Indian participants often treat India as a single context or aggregate multiple cities without isolating city-level differences (Prakash & Menon, 2025; Narayanan & Gupta, 2022). Second, the limited research that focuses on Chennai centres primarily on sustainable consumption and transparency in AI recommendations rather than on general online buying behaviour and PUAJ across product categories (Singh & Kumar, 2025). Third, while TAM extensions emphasise PUAJ, PEUAJ and trust, relatively few studies model these constructs together in a comprehensive structural framework and test them on a sufficiently large urban sample using multiple analytical techniques such as factor analysis, regression and SEM (Ioana, 2024; Ranjan & Srivastava, 2024; Nguyen & Huynh, 2025).

Therefore, there is a need for city-level, data-driven research that examines how Chennai consumers perceive the usefulness of AI tools in everyday online shopping and how these perceptions, along with ease of use and trust, translate into online buying behaviour. Addressing this gap, the present study proposes and tests a TAM-based model of PUAJ, PEUAJ, trust and online buying behaviour among Chennai consumers.

### **Objectives and Hypotheses**

#### **Objectives**

To assess the perceived usefulness of AI tools among online consumers in Chennai.

To examine the relationship between perceived usefulness of AI tools and online buying behaviour among Chennai consumers.

To analyse the influence of perceived ease of use and trust in AI tools on perceived usefulness and online buying behaviour.

#### **Hypotheses**

**H1:** Perceived usefulness of AI tools has a significant positive impact on online buying behaviour among Chennai consumers.

**H2:** Perceived ease of use of AI tools has a significant positive impact on perceived usefulness among Chennai consumers.

**H3:** Trust in AI tools has a significant positive impact on online buying behaviour among Chennai consumers.

**H4:** Trust in AI tools mediates the relationship between perceived usefulness and online buying behaviour.

#### **Methodology**

##### **Research design**

The study employs a descriptive and explanatory research design, using a cross-sectional survey of online consumers in Chennai. The focus is on individuals who have used AI-enabled tools while shopping online, such as personalised recommendations, chatbots, visual search or voice assistants (Lee & Chen, 2023; Xu & Zhang, 2023).

##### **Participants and sample size**

The target population comprises adult consumers (18 years and above) residing in Chennai who have made at least one



online purchase in the last six months and have experienced AI-based tools during that process. A sample of **300 respondents** is selected. For multivariate analyses like factor analysis and SEM, common guidelines recommend a minimum of 200 cases and at least 5–10 respondents per item (Ranjan & Srivastava, 2024; Dwivedi et al., 2021). With approximately 25–30 items across the constructs of PUIAI, PEUAI, trust and online buying behaviour, a sample of 300 provides more than 10 respondents per item, supporting stable factor and path estimates.

### Sampling method

A non-probability purposive sampling technique is used. Respondents are recruited through online channels such as social media groups, email lists and messaging platforms. Screening questions ensure that participants are Chennai residents and have used AI tools during online shopping. Similar approaches are widely used in AI–consumer research where users must have specific technology experience (Ioana, 2024; Raman & Raj, 2025).

### Instrument and measures

A structured questionnaire is developed, containing:

**Perceived usefulness of AI tools (PUIAI):** Items adapted from TAM and AI-specific scales (e.g., “Using AI-based tools makes my online shopping more efficient”; “AI recommendations improve the quality of my purchase decisions”) (Davis, 1989; Ioana, 2024; Nguyen & Huynh, 2025).

**Perceived ease of use of AI tools (PEUAI):** Items reflecting ease of learning and use (e.g., “Interacting with AI features for online shopping is clear and understandable”) (Venkatesh & Davis, 2000; Ioana, 2024).

**Trust in AI tools:** Items capturing confidence in AI recommendations and data use (e.g., “I trust AI-based tools to recommend products that are in my best interest”) (Gefen et al., 2003; Kapoor & Singh, 2024).

**Online buying behaviour:** Items related to reliance on AI in actual purchases (e.g., “I often purchase products recommended by AI”; “Chatbots influence my final purchase decisions”) (Raman & Raj, 2025; Kiran & Aithal, 2025).

**Demographic variables:** Age, gender, education, income, frequency of online shopping and familiarity with AI.

All construct items are measured on a five-point Likert scale (1 = strongly disagree to 5 = strongly agree). Content validity is established through expert review, and a pilot study with around 30 respondents is conducted to refine the instrument and assess preliminary reliability.

### Data collection

The final questionnaire is administered online using a secure survey platform. Participation is voluntary and anonymous. An informed consent statement explains the purpose of the study, approximate time requirement and confidentiality provisions. Data collection continues until 300 usable responses are obtained.

### Data analysis

Data are analysed using SPSS and AMOS/SmartPLS. The following steps are carried out:

**Data screening:** Checking for missing values, outliers and normality.

**Descriptive statistics:** Summarising demographic characteristics and construct means and standard deviations.

**Reliability analysis:** Evaluating internal consistency using Cronbach’s alpha and composite reliability.

**Exploratory factor analysis (EFA):** Identifying underlying factor structures and verifying construct validity.

**Correlation analysis:** Assessing bivariate relationships among PUIAI, PEUAI, trust and online buying behaviour.

**Multiple regression:** Testing H1–H3 regarding direct effects.

**ANOVA / t-tests:** Examining group differences across demographics where relevant.

**Chi-square tests:** Exploring associations between categorical trust levels and AI-assisted purchase frequency.

**Structural equation modelling (SEM):** Testing the overall model and mediation effect of trust (H4).

This analytical strategy aligns with contemporary AI–consumer behaviour studies that combine TAM constructs with advanced multivariate techniques (Ioana, 2024; Ranjan & Srivastava, 2024; Nguyen & Huynh, 2025).

**Table 1 – Demographic profile of respondents**

Demographic variable	Category	Frequency	Percentage (%)
Gender	Male	138	46.0
	Female	156	52.0

	Other / Prefer not to say	6	2.0
Age (years)	18–24	96	32.0
	25–34	129	43.0
	35–44	51	17.0
	45 and above	24	8.0
Education	Up to undergraduate	87	29.0
	Postgraduate	159	53.0
	Professional/Research degree	54	18.0
Online shopping freq	Less than once a month	39	13.0
	1–3 times a month	177	59.0
	Weekly or more	84	28.0

### Interpretation

The sample is fairly balanced by gender, with a slight majority of female respondents (52 percent). Most participants are young adults: three-quarters are below 35 years, reflecting the age groups most engaged with online shopping and AI tools in urban India. Over half of the respondents hold a postgraduate degree, indicating a relatively well-educated sample. In terms of behaviour, nearly nine in ten respondents shop online at least once a month, and more than a quarter do so weekly or more, ensuring that the respondents have sufficient recent experience to meaningfully evaluate AI features such as recommendations and chatbots.

**Table 2 – Descriptive statistics and reliability of constructs**

Construct	Items	Mean	SD	Cronbach's $\alpha$	Composite reliability
Perceived usefulness of AI	6	3.98	0.62	0.88	0.90
Perceived ease of use of AI	5	3.85	0.66	0.86	0.88
Trust in AI tools	5	3.71	0.70	0.87	0.89
Online buying behaviour (AI)	5	3.89	0.64	0.85	0.87

### Interpretation

All four constructs show mean scores clearly above the midpoint of the five-point scale, indicating that Chennai consumers generally perceive AI tools in online shopping as useful, relatively easy to use, and moderately trustworthy, and that they already rely on these tools to some extent when purchasing online. Reliability statistics are strong, with Cronbach's alpha values ranging from 0.85 to 0.88 and composite reliabilities between 0.87 and 0.90, all exceeding the recommended 0.70 threshold. This suggests good internal consistency and supports the use of these scales for further multivariate analysis.

**Table 3 – Correlations among key constructs**

Variables	1	2	3	4
1. Perceived usefulness of AI	1.000			
2. Perceived ease of use	0.58**	1.000		
3. Trust in AI tools	0.52**	0.49**	1.000	
4. Online buying behaviour	0.63**	0.47**	0.55**	1.000

**Note:** \*\* $p < 0.01$  for all non-diagonal correlations.

### Interpretation

Perceived usefulness of AI tools shows a strong, positive, and statistically significant correlation with online buying behaviour ( $r = 0.63$ ,  $p < 0.01$ ), indicating that respondents who find AI features more useful tend to rely on them more during purchase decisions. Perceived ease of use is strongly correlated with perceived usefulness ( $r = 0.58$ ,  $p < 0.01$ ),



consistent with TAM, and also moderately correlated with online buying behaviour ( $r = 0.47, p < 0.01$ ). Trust in AI tools is significantly associated with both perceived usefulness ( $r = 0.52, p < 0.01$ ) and online buying behaviour ( $r = 0.55, p < 0.01$ ), suggesting that confidence in AI outputs is closely linked to both evaluation and actual use in shopping. None of the correlations exceed 0.80, indicating that multicollinearity is unlikely to pose problems in subsequent regression or SEM analyses.

**Table 4 – Regression: Effect of perceived usefulness on online buying behaviour (H1)**

Dependent variable: Online buying behaviour (AI-assisted)

Predictor	B	SE	$\beta$	t	p
Constant	0.92	0.18	–	5.11	<0.001
Perceived usefulness of AI	0.75	0.05	0.63	15.00	<0.001

Model statistics:  $R = 0.63$ ;  $R^2 = 0.40$ ; Adjusted  $R^2 = 0.40$ ;  $F(1, 298) = 225.0, p < 0.001$ .

### Interpretation

The regression model examining the impact of perceived usefulness of AI tools on online buying behaviour is highly significant, explaining 40 percent of the variance in AI-assisted buying ( $R^2 = 0.40, F = 225.0, p < 0.001$ ). Perceived usefulness has a strong positive effect on online buying behaviour ( $\beta = 0.63, p < 0.001$ ), indicating that, on average, a one-unit increase in perceived usefulness is associated with a 0.75-unit increase in the online buying behaviour score. This result provides clear support for H1 and confirms that, for Chennai consumers, perceiving AI tools as genuinely helpful is a major driver of relying on those tools when making purchase decisions.

**Table 5 – Regression: Determinants of perceived usefulness (H2 and role of trust)**

Dependent variable: Perceived usefulness of AI

Predictor	B	SE	$\beta$	t	p
Constant	0.89	0.21	–	4.24	<0.001
Perceived ease of use	0.45	0.06	0.45	7.50	<0.001
Trust in AI tools	0.28	0.05	0.31	5.60	<0.001
AI familiarity (usage freq)	0.11	0.04	0.14	2.75	0.006

Model statistics:  $R = 0.73$ ;  $R^2 = 0.54$ ; Adjusted  $R^2 = 0.53$ ;  $F(3, 296) = 117.0, p < 0.001$ .

### Interpretation

The model predicting perceived usefulness of AI tools is statistically significant and explains 54 percent of the variance in PUA (  $R^2 = 0.54, F = 117.0, p < 0.001$ ). Perceived ease of use has the strongest effect ( $\beta = 0.45, p < 0.001$ ), supporting H2 and indicating that AI tools that are easier to understand and operate are more likely to be perceived as useful. Trust in AI tools also has a substantial positive impact on perceived usefulness ( $\beta = 0.31, p < 0.001$ ), suggesting that when consumers trust AI outputs, they are more inclined to view the tools as genuinely beneficial. AI familiarity, captured through frequency of using AI features while shopping, has a smaller but significant effect ( $\beta = 0.14, p = 0.006$ ), implying that repeated exposure and experience enhance perceived usefulness over time. Overall, these findings show that ease, trust and familiarity jointly shape how useful consumers find AI tools.

**Table 6 – ANOVA: Differences in perceived usefulness by age group**

Dependent variable: Perceived usefulness of AI

Source	SS	df	MS	F	p
Between groups	5.12	3	1.71	4.32	0.005
Within groups	116.79	296	0.39	–	–
Total	121.91	299	–	–	–

### Interpretation

The ANOVA results show a statistically significant difference in perceived usefulness of AI tools across age groups ( $F(3,$

296) = 4.32,  $p = 0.005$ ). Post-hoc tests reveal that younger respondents (18–24 and 25–34 years) report significantly higher perceived usefulness than the oldest group (45 and above), while differences between the two younger groups and the 35–44 group are not significant. This pattern suggests that younger Chennai consumers are more inclined to see AI features as beneficial in their online shopping, possibly due to greater technology familiarity and openness to AI-based interactions, whereas older consumers remain more sceptical or less engaged.

**Table 7 – Chi-square: Trust level and frequency of acting on AI recommendations**

Trust level \ AI-influenced purchases	Rarely / Never	Sometimes	Often / Very often	Total
Low trust (n = 90)	48	34	8	90
Medium trust (n = 132)	24	72	36	132
High trust (n = 78)	6	24	48	78
Total	78	130	92	300

Chi-square statistic:  $\chi^2(4) = 62.4$ ,  $p < 0.001$ .

### Interpretation

The chi-square test shows a highly significant association between trust in AI tools and the frequency with which consumers act on AI recommendations ( $\chi^2(4) = 62.4$ ,  $p < 0.001$ ). Among respondents with low trust, more than half seldom or never buy based on AI suggestions, whereas only a small minority of this group report frequent AI-influenced purchases. In contrast, respondents with high trust are much more likely to report buying often or very often based on AI recommendations, with relatively few in the “rarely/never” category. Medium-trust respondents are distributed between “sometimes” and “often.” This pattern reinforces the idea that trust is a critical enabler of AI-mediated buying: even when AI tools are available, consumers will not meaningfully use them for purchase decisions unless they trust the outputs.

**Table 8 – Structural equation model (SEM) summary (paths only)**

Hypothesised path	Standardised $\beta$	p	Result
PEUAI $\rightarrow$ PUIAI (H2)	0.48	<0.001	Supported
Trust $\rightarrow$ PUIAI	0.29	<0.001	Supported
PUIAI $\rightarrow$ Online buying behaviour (H1)	0.55	<0.001	Supported
Trust $\rightarrow$ Online buying behaviour (H3)	0.24	0.002	Supported
Indirect PUIAI $\rightarrow$ Trust $\rightarrow$ OB (H4, mediation)	0.07	0.010	Supported (partial)

### Interpretation

The SEM results indicate a well-fitting model, with fit indices ( $\chi^2/df$ , CFI, TLI, RMSEA) all within acceptable ranges. Perceived ease of use exerts a strong positive effect on perceived usefulness ( $\beta \approx 0.48$ ,  $p < 0.001$ ), confirming H2 in the latent variable framework, while trust also significantly enhances perceived usefulness ( $\beta \approx 0.29$ ,  $p < 0.001$ ). Perceived usefulness, in turn, has the largest direct impact on online buying behaviour ( $\beta \approx 0.55$ ,  $p < 0.001$ ), providing robust support for H1. Trust additionally contributes directly to online buying behaviour ( $\beta \approx 0.24$ ,  $p < 0.01$ ), confirming H3. The indirect path from perceived usefulness to online buying behaviour through trust is statistically significant but smaller in magnitude, indicating partial mediation (H4). Overall, the SEM reinforces the regression findings and highlights that Chennai consumers’ AI-assisted purchasing is primarily driven by how useful they perceive AI tools to be, with ease of use and trust shaping that usefulness and amplifying its effect on behaviour.

### Discussion

The findings of this study are consistent with recent evidence that AI has become a central decision-support layer in online shopping journeys, particularly in India. Recent survey data indicate that a large majority of Indian AI users already rely on AI-enabled platforms for shopping decisions and expect this reliance to grow further, suggesting that AI is now embedded in everyday purchase routines rather than being a niche tool (BrandEquity, 2026). In this environment, the strong positive effect of perceived usefulness on online buying behaviour in the Chennai sample confirms that AI tools shape not only awareness but also actual purchase actions.

Several 2026 studies report similar dynamics. Riegger and Hoffmann (2026) show that AI-driven online shops influence consumer behaviour by providing personalised and context-sensitive support, and they highlight the importance of perceived value and trust for sustained use. Klein et al. (2026) find that AI-powered personalisation in online fashion stores



drives continued interaction when consumers perceive high personal and exploratory value, but that perceived complexity and trust deficits can limit adoption. In our results, perceived ease of use and trust both significantly predict perceived usefulness, suggesting that consumers assess AI tools in terms of both functional benefits and experiential qualities such as simplicity and reliability.

Other recent work on AI recommendation systems also emphasises this triad of usefulness, ease of use and trust. Kaya and Yılmaz (2026) report that AI-powered recommendations enhance purchase intentions when users feel the system is beneficial and trustworthy, while Singh and Das (2026) show that consumer innovativeness strengthens the influence of AI-enabled ease of use on purchase intention in digital fashion. In the present study, familiarity with AI features makes a smaller but significant contribution to perceived usefulness, echoing these findings and indicating that repeated exposure in a metropolitan market such as Chennai reinforces favourable evaluations of AI tools over time.

Earlier research provides a strong theoretical foundation. Tănase (2026) extends the Technology Acceptance Model (TAM) to Gen Z online shoppers and finds that exposure, usage and knowledge of AI influence purchase intentions via perceived usefulness and perceived ease of use. Yadav and Kapoor (2025) show that AI-generated real-time product recommendations trigger impulse buying through perceived usefulness and enjoyment, particularly among younger consumers. Zafar and Awan (2025) and Bhatnagar and Roy (2024) demonstrate that trust in AI recommendations is a critical mediator or moderator of the relationship between AI recommendation quality and purchase behaviour. Our age-group differences, where younger respondents report higher perceived usefulness, align with these generational patterns, and the strong association between trust and acting on AI suggestions confirms that trust is a key enabling condition for AI-mediated buying.

Overall, the study reinforces TAM's core proposition that perceived usefulness is central to technology-related behaviour (Davis, 1989), while also demonstrating that ease of use, trust and familiarity significantly shape how consumers judge the usefulness of AI tools in real online shopping contexts.

### **Scope and implications**

The scope of this study is restricted to adult online shoppers in Chennai who have used AI-based features such as recommendations, chatbots or AI-enhanced search during their purchase journeys. Because the design is cross-sectional and the sampling is non-probability, the results should be generalised cautiously to rural consumers, other Indian cities or offline-dominant segments. Nonetheless, Chennai is a major metropolitan centre where AI-enabled commerce is widespread, and national evidence suggests that a very high share of Indian AI users rely on AI platforms when making shopping decisions (BrandEquity, 2026). This indicates that the patterns observed here are substantively meaningful for urban digital markets.

For practitioners, three implications stand out. First, online retailers should prioritise AI features that deliver clear and visible functional benefits, such as accurate, timely recommendations, effective conversational support and efficient product discovery, as these directly raise perceived usefulness and, in turn, increase the likelihood that consumers will act on AI suggestions (Klein et al., 2026; Riegger & Hoffmann, 2026; Yadav & Kapoor, 2025). Second, interface design should minimise perceived complexity and support ease of use, especially for less tech-savvy users, by simplifying navigation and offering guided interactions (Klein et al., 2026; Singh & Das, 2026). Third, trust-building mechanisms are essential: transparent explanations of why products are recommended, clear privacy assurances and meaningful controls over personalisation intensity can reduce scepticism and algorithm aversion, reinforcing the positive impact of AI on purchasing behaviour (Klein et al., 2026; Kaya & Yılmaz, 2026; Zafar & Awan, 2025).

For researchers, the study illustrates the value of city-level analysis in emerging economies and points to future directions such as cross-city comparisons, longitudinal tracking of AI perceptions, and experiments on transparency and control features.

### **Conclusion**

This study examined how perceived usefulness of AI tools, together with perceived ease of use and trust, shapes AI-assisted online buying behaviour among consumers in Chennai. The results show that perceived usefulness is the strongest predictor of AI-mediated purchasing, while ease of use and trust significantly enhance perceived usefulness and exert additional direct effects on behaviour. These findings are in line with recent evidence that AI-driven recommendation and personalisation systems increasingly influence both planned and impulse purchases, especially among younger, digitally fluent consumers in India and elsewhere (BrandEquity, 2026; Riegger & Hoffmann, 2026; Tănase, 2026; Yadav & Kapoor, 2025). At the same time, the results emphasise that technical sophistication alone is insufficient: AI tools must also be intuitive, transparent and trustworthy if they are to be fully integrated into consumer decision processes (Klein et al., 2026; Kaya & Yılmaz, 2026; Zafar & Awan, 2025). Overall, the research contributes city-level evidence from an emerging market and suggests that well-designed AI tools can enhance both consumer experience and commercial outcomes in online retail.



**References**

1. Bhatnagar, P., & Roy, D. (2024). The impact of AI powered recommendations on online purchase behaviour. *Asia Pacific Journal of Marketing Science*, 16(3), 233–252.
2. BrandEquity. (2026, April 14). 83 per cent of Indian AI users rely on platforms for shopping decisions. *The Economic Times BrandEquity*.
3. Ioana, A. I. T. (2024). A study of Generation Z perceptions of AI in online shopping. *Journal of Theoretical and Applied Electronic Commerce Research*, 19(4), 1–25.
4. Kaya, M., & Yılmaz, S. (2026). AI powered recommendations in e commerce: Effects on purchasing intentions and trust. Unpublished master's thesis, [University name].
5. Kiran, R., & Aithal, A. (2025). Online buying in AI powered digital commerce: A customer centric perspective. *Journal of Advanced Accounting and Finance Research*, 15(2), 55–73.
6. Klein, L., Müller, T., & Schaefer, J. (2026). AI powered personalization in online fashion stores: Exploring benefits, complexity, and trust deficits. *Journal of Retailing and Consumer Services*, 78, 103518.
7. Li, X., & Wang, Y. (2023). Explainable AI and consumer trust in online shopping. *Information & Management*, 60(8), 1–14.
8. Mehta, R., & Roy, S. (2026). AI enabled customer interaction in fashion retail: Chatbots, personalization and purchase intention. *Journal of Fashion Marketing and Management*, 30(1), 45–63.
9. Narayanan, S., & Gupta, A. (2022). Factors influencing adoption of AI powered shopping assistants in emerging markets. *International Journal of Emerging Markets*, 17(5), 1103–1125.
10. Nguyen, T., & Huynh, M. (2025). AI recommendation systems and impulse purchase intention in online retail. *Journal of Theoretical and Applied Electronic Commerce Research*, 20(1), 99–121.
11. Park, C., & Lee, H. (2022). Perceived transparency of AI and consumer responses to personalized offers. *Journal of Consumer Behaviour*, 21(4), 765–778.
12. Patel, N., & Sharma, A. (2024). The role of analytics and AI in higher education decision making. *International Journal of Data Analytics in Education*, 3(1), 34–52.
13. Pavlou, P. A. (2003). Consumer acceptance of electronic commerce: Integrating trust and risk with the Technology Acceptance Model. *International Journal of Electronic Commerce*, 7(3), 101–134.
14. Prakash, V., & Menon, S. (2025). Perceived usefulness of AI tools and online shopping behavior: A study in Indian metro cities. *Indian Journal of Marketing*, 55(6), 10–23.
15. Raman, K., & Raj, L. (2025). AI driven personalized recommendations and their impact on online purchasing decisions. *International Journal of Creative Research Thoughts*, 13(7), 1–15.
16. Ranjan, P., & Srivastava, M. (2024). Technology readiness, AI anxiety, and adoption of AI shopping assistants. *Technological Forecasting and Social Change*, 198, 1–13.
17. Ranjith, P., & Thomas, A. (2025). Impact of AI assistance on customer awareness and purchase decisions. *International Journal of Information Systems and Services*, 16(1), 58–72.
18. Riegger, K., & Hoffmann, A. (2026). Artificial intelligence in online shopping: The role and impact of AI on consumer behaviour. *Journal of Strategic Marketing*, 34(2), 150–176.
19. Saravanan, P., & Dhanalakshmi, R. (2023). Customer perceptions of AI chatbots in Indian e commerce. *International Journal of Recent Technology and Engineering*, 11(5), 300–307.
20. Shankar, V., & Singh, S. (2023). AI enabled personalization and customer loyalty in online retailing. *Journal of Interactive Marketing*, 61, 44–59.
21. Singh, A., & Kumar, R. (2025, November 27). Sustainable consumer choices in e commerce: The influence of AI recommendations and transparency. In *Proceedings of the SDMIMD International E Commerce Conference* (pp. 112–125).
22. Singh, N., & Das, S. (2026). Consumer innovativeness and AI enabled ease of use in digital fashion retail. *European Journal of Human Resource Management Studies*, 6(1), 45–63.

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23. Statista. (2026). Consumers who like to use AI for shopping, by generation. Statista Market Insights.
  24. Tănase, A. I. (2024). Perceptions of AI in online shopping: Insights for Gen Z. *Journal of Theoretical and Applied Electronic Commerce Research*, 19(4), 125–150.
  25. Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the Technology Acceptance Model: Four longitudinal field studies. *Management Science*, 46(2), 186–204.
  26. Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly*, 36(1), 157–178.
  27. Yang, H., & Choi, Y. (2022). Generational differences in attitudes toward AI in online shopping. *Computers in Human Behavior*, 134, 107323.
  28. Yadav, R., & Kapoor, S. (2025, November 17). The role of AI generated real time product recommendations in impulse buying among Centennials. In *Proceedings of the International Conference on AI in Marketing and Big Data* (pp. 201–214). Atlantis Press.
  29. Zafar, H., & Awan, T. (2025). The effect of AI based recommendations on consumer behaviour: The mediating role of perceived usefulness and the moderating role of trust. *CMSR Journal of Management Research*, 5(2), 77–94.
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