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Role of artificial intelligence on consumer buying behavior: the dual effects of AI-enabled features on decision-making and trust

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Abstract

Purpose – This study investigates the influence of Artificial Intelligence (AI) features on consumers' buying behavior for electronic products, with a specific focus on consumer trust, decision-making ease, and purchase intention.

Design/methodology/approach – This study used a quantitative research design to investigate the impact of key AI features on consumer outcomes. Data were collected using a structured questionnaire. Structural Equation Modeling (SEM) was employed to analyze the relationships between three AI features (modeled as latent constructs for recommendation engines, chatbots, and comparison tools) and the dependent variables of consumer trust, perceived decision-making support, and purchase intention.

Findings – The results indicate that AI-enabled features significantly enhance consumer confidence and satisfaction by simplifying product evaluations and increasing perceived usefulness. However, concerns about privacy risks, overreliance on technology, and decision fatigue continue to shape consumer trust and adoption. This study highlights the importance of designing AI systems that are transparent, ethical, and inclusive for both tech-savvy and less technologically adept consumers.

Originality/value – The originality of this study is threefold. First, it developed a unified framework that integrates technology acceptance and trust-based perspectives, a synthesis rarely found in the existing literature. Second, it moves beyond examining AI as a monolith by investigating how distinct and common AI features (recommendation engines, chatbots, and comparison tools) jointly influence the consumer decision journey. Finally, it bridges a critical theoretical gap by elucidating the interplay between perceived usefulness, trust, and ethical design, providing novel insights into how AI can be implemented not only effectively but also responsibly to empower consumers.

Keywords Artificial intelligence, Consumer behavior, Electronic products, Decision-making, Trust, Purchase intention

Paper type Research article

1. Introduction

Digital transformation and Artificial Intelligence (AI) have a profound influence on society and business (Jain *et al*., 2021; Paul *et al*., 2021; 2024; Patil *et al*., 2025; Sharma *et al*., 2025; Raman and Paul, 2025). AI refers to the simulation of human intelligence in machines that are capable of learning, reasoning, and problem-solving (Russell and Norvig, 2020). Contemporary AI systems leverage advanced algorithms to process large datasets, recognize patterns, make data-driven decisions, and improve performance with minimal human intervention (Haenlein and Kaplan, 2019). Core AI domains include Machine Learning (ML), which enables systems to learn from data without explicit programming; Natural

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Language Processing (NLP), which allows machines to understand and generate human language; and computer vision, which facilitates the interpretation of visual information (Szeliski, 2022). While these technologies provide the technical foundation of AI, the present study does not focus on their engineering characteristics. Instead, AI is conceptualized as a *consumer-facing enabler* whose influence is manifested through how individuals perceive, understand, and respond to AI-driven applications in market settings.

AI has transformed industries by automating processes, enhancing efficiency, and enabling data-driven innovation. In everyday consumer life, AI underpins smart devices, virtual assistants, recommendation systems, and driver assistance technologies. Prior research indicates that consumers are more likely to accept AI when they perceive it as useful, affordable, and easy to use (Sharma *et al*., 2025). Although ethical and privacy concerns persist, AI continues to reshape sectors such as business, healthcare, finance, and education. In marketing and retail contexts, AI facilitates predictive analytics, personalized communication, and customized engagement, directly influencing how consumers search for information, evaluate alternatives, and make purchase decisions in digital environments (Ramya and Karthikeyan, 2024).

Within this broader landscape, the consumer electronics sector represents a particularly dynamic context for examining AI'simpact on buying behavior. Purchasing decisions for electronic products are shaped by a combination of technological sophistication, perceived value, and brand trust. Consumers increasingly seek products that integrate advanced features with reliability, usability, and strong after-sales support, leading to sustained loyalty toward established brands such as Apple, Samsung, and Sony (Eastman *et al*., 2023). AI further strengthens brand–consumer relationships by enabling firms to analyze customer journeys, personalize recommendations, and optimize engagement strategies, thereby influencing how consumers perceive value and compare competing offerings.

As digital literacy and online shopping adoption have increased, consumers have become more comfortable engaging with AI-enabled platforms. Studies highlight that factors such as platform trust, convenience, and price advantages significantly influence online purchase behavior, even as concerns related to security and physical product inspection persist (Rungsrisawat *et al*., 2019). Recent research underscores that understanding AI-driven purchase patterns is critical for aligning marketing strategies with evolving consumer expectations (Meddah, 2024; Sharma *et al*., 2024). In competitive markets, AI-powered insights enable firms to better comprehend consumer motivations, optimize promotions, and address price sensitivity, particularly in high-involvement categories such as consumer electronics.

Despite these advancements, important research gaps remain. Existing studies largely emphasize the benefits of AI-enabled personalization and engagement, while insufficiently addressing countervailing concerns. These include the erosion of consumer trust due to privacy risks, the potential for decision fatigue arising from excessive algorithmic recommendations, and the tendency of prior research to focus predominantly on technologically sophisticated users. Consequently, there is limited understanding of how varying levels of AI awareness interact with other purchase-influencing factors to shape consumer decision-making in the electronics market.

Against this backdrop, *the present study investigates the role of consumer awareness and perceptions of AI-driven applications in shaping buying behavior within the consumer electronics sector*. Rather than examining technical attributes of AI, the study focuses on how consumers' understanding of AI, combined with factors such as trust, price sensitivity, and promotional influence, affects their purchasing decisions. Accordingly, the research is guided by the following questions.

RQ1. How aware are consumers of AI, and how does this awareness influence their purchasing decisions for electronic products?

RQ2. What is the relationship between AI awareness, other influencing factors, and overall consumer buying behavior?

By addressing these questions, the study aims to advance academic understanding of AI'sbehavioral implications while offering practical insights for developing AI-driven marketing systems that are transparent, trustworthy, and inclusive.

2. Literature review

In recent years, AI has emerged as a transformative force in e-commerce, fundamentally altering how firms analyze, predict, and influence consumer behavior (Paul *et al*., 2024; Sharma *et al*., 2025). Existing literature highlights AI'srole not merely as a technological tool but as a strategic mechanism that reshapes consumer decision-making through personalization, predictive analytics, and real-time engagement. This section synthesizes prior research using a structured thematic approach to establish the theoretical foundation and identify unresolved gaps.

2.1 AI-enabled tools and consumer decision-making

A substantial body of research examines how AI-enabled tools—such as chatbots, recommendation systems, adaptive pricing, and targeted advertising—affect consumer decision-making. Studies consistently show that these tools enhance decision efficiency by reducing search costs and providing real-time, personalized support (Canhoto *et al*., 2023). Such systems improve perceived usefulness and convenience, leading to higher satisfaction and conversion rates.

Advancements in generative AI have further expanded these capabilities. Madanchian (2024a, b) demonstrated that models such as Generative Adversarial Networks (GANs) and transformer architectures enable sophisticated prediction of consumer preferences, facilitating highly customized shopping experiences. However, these benefits are counterbalanced by concerns related to computational intensity, privacy, and ethical data usage, which may inhibit widespread adoption.

From a psychological perspective, Hallikainen *et al*. (2023) found that while AI-driven personalization enhances trust and satisfaction, excessive or overly complex recommendations may lead to decision fatigue. This highlights the need for AI system designs that balance relevance with cognitive simplicity to support rather than overwhelm consumers.

2.2 AI in high-involvement purchase contexts: consumer electronics

High-involvement product categories, such as consumer electronics, provide a particularly relevant context for examining AI-driven decision-making. Purchases in this category involve higher financial risk, extensive information processing, and greater reliance on evaluative cues such as reviews and comparisons.

Prakash and Singh (2023) showed that AI-integrated platforms offering comparative analysis, predictive recommendations, and peer reviews significantly reduce decision-making time and enhance purchase confidence. However, the authors caution that excessive reliance on AI may diminish independent judgment, increasing consumer dependency on automated systems.

From the retailer's perspective, Li *et al*. (2023) highlighted how AI-driven insights improve pricing strategies, inventory optimization, and demand forecasting in electronics retailing. Despite these operational advantages, their findings reveal a potential exclusionary effect, as standardized AI interfaces may alienate less technologically proficient consumers, reinforcing a digital divide.

2.3 Personalisation, trust, and fairness in AI systems

Personalization represents one of AI'smost influential mechanisms in shaping consumer behavior. Wang and Zhou (2023) demonstrated that AI-driven personalization enhances customer loyalty and repeat purchase intentions, provided consumers trust how their data are collected and utilized. Trust thus emerges as a critical mediator between AI functionality and behavioral outcomes.

Ethical design considerations further shape consumer perceptions. Kumar and Jain (2022) found that perceptions of fairness and transparency significantly influence acceptance of AI systems. While AI reduces choice overload and enhances convenience, algorithmic bias and opque decision logic undermine perceived fairness. Supporting these findings, Zhang *et al*. (2022) showed that predictive analytics can reduce cart abandonment by offering timely recommendations and incentives, but adoption depends heavily on perceived data security. Together, these studies emphasize that trust, privacy, and fairness are not peripheral concerns but foundational to AI effectiveness in consumer contexts.

2.4 Cross-cultural and consumer segmentation considerations

Recent studies have begun to investigate how AI adoption and efficacy vary across demographics and cultures. Similarly, Park and Kim (2022) demonstrated that AI tools such as chatbots and virtual try-ons significantly enhance engagement and conversion rates, but only when algorithms are continuously updated to match evolving consumer expectations. These findings underscore the importance of segmentation and cross -cultural adaptive design in AI deployment.

Cross-cultural and demographic studies further reinforce this view. Research applying the Technology Acceptance Model (TAM) suggests that trust may outweigh ease of use as a determinant of AI adoption in certain cultural contexts, challenging conventional adoption hierarchies (Nagy and Hajdu, 2022). Age, engagement intensity, and digital familiarity consistently emerge as key moderators of AI effectiveness (Khan *et al*., 2023; Abdullah, 2024).

2.5 Synthesis and identified gaps

Overall, the literature confirms AI'ssignificant potential to shape consumer behavior through personalization, predictive analytics, and decision simplification. Key enablers include perceived usefulness, trust, transparency, and relevance. At the same time, persistent risks, such as privacy concerns, algorithmic bias, decision fatigue, and digital exclusion, remain insufficiently addressed.

Three critical gaps emerge. First, despite the acknowledged importance of trust, there is a lack of integrated frameworks that provide consumers with meaningful control over their data. Second, while decision fatigue is recognized, limited guidance exists on how AI systems can be designed to mitigate cognitive overload. Third, the predominant focus on technologically proficient consumers leaves limited understanding of how less tech-savvy users perceive and engage with AI-driven systems.

The interlinking of research articles offers a strong narrative around how AI is not merely a tool in e-commerce, but an invisible architect that designs how consumers make decisions, particularly in the field of electronics, with less attention given to how less technologically inclined groups engage with AI systems, highlighting the need for more inclusive AI solutions.

Addressing these gaps, the present study examines how *consumer awareness and perceptions of AI, particularly trust, usefulness, ease of use, and personalization, collectively influence buying behavior in the consumer electronics sector,* thereby contributing to both theory and responsible AI practice.

2.6 Theoretical and construct definitions and hypothesis development

2.6.1 Definitions. Based on the review of extant literature and the objectives of the study, the following variables were identified.

2.6.1.1 Independent variables. *AI awareness*: These variable captures consumers' understanding and familiarity with the application of AI in electronic product marketing and purchasing environments. Prior research suggests that awareness of AI enhances perceived usefulness and reduces uncertainty in technology-mediated decision-making (Sharma *et al*., 2024; Meddah, 2024). *Influencing factors*: This construct represents key determinants that shape consumer buying behavior in AI-enabled contexts, including perceived usefulness, ease of use, trust, personalization, price sensitivity, promotions, and online platform credibility. These factors are well-established antecedents of technology adoption and purchase intention (Davis, 1989; Wang and Zhou, 2023).

2.6.1.2 Dependent variable. *Consumer buying behavior:* This refers to consumers' tendency to search for, evaluate, and purchase electronic products through AI-enabled platforms. It reflects both attitudinal and behavioral responses toward AI-assisted purchasing environments (Prakash and Singh, 2023).

2.6.1.3 Theoretical and construct definitions. The constructs in our study are theoretically grounded and measured using validated scales from prior literature. *AI Awareness* is defined based on technology awareness and readiness research, capturing consumers' understanding of AI functionalities in electronic product marketing rather than general technological attitudes (Davis, 1989; Parasuraman, 2000; Sharma *et al*., 2024; Meddah, 2024). *Influencing Factors* is a higher-order construct encompassing perceived usefulness and ease of use (TAM; Davis, 1989), trust (Gefen *et al*., 2003; Wang and Zhou, 2023), personalization (Bleier *et al*., 2018), price sensitivity (Lichtenstein *et al*., 1993), promotional responsiveness, and online platform credibility (Pavlou, 2003). *Consumer Buying Behavior* is operationalized as a multidimensional construct, capturing both attitudinal (evaluation, preference) and behavioral (information search, purchase intention) dimensions (Prakash and Singh, 2023). This operationalization is theoretically justified as it aligns with established frameworks and reflects the multidimensional nature of AI-influenced consumer behavior.

2.6.2 Hypothesis development. 2.6.2.1 AI awareness and demographic differences. Consumer awareness of AI is not uniformly distributed across populations. Prior studies indicate that demographic characteristics such as age, education, income, and digital literacy significantly influence individuals' exposure to and understanding of AI technologies (Nagy and Hajdu, 2022; Mehta and Gupta, 2022). Younger and more educated consumers tend to exhibit higher AI awareness due to greater digital engagement, whereas older or less technologically familiar consumers often display lower awareness levels.

Accordingly, the following hypothesis is proposed.

H1. There is a significant difference in consumers' AI awareness across demographic factors.

2.6.2.2 AI awareness, influencing factors, and buying behavior. The TAM posits that awareness and understanding of technology shape perceptions of usefulness and ease of use, which subsequently influence behavioral intentions (Davis, 1989). In AI-driven marketing contexts, awareness enhances consumers' ability to evaluate algorithmic recommendations, thereby strengthening trust and perceived control (Hallikainen *et al*., 2023).

Moreover, empirical studies suggest that AI awareness interacts with influencing factors such as personalization, trust, and price sensitivity to shape consumer decision-making. For instance, AI-driven personalization has been shown to positively affect purchase behavior when consumers are aware of and comfortable with AI processes (Wang and Zhou, 2023). Conversely, low awareness may amplify privacy concerns and reduce the effectiveness of AI-enabled recommendations (Kumar and Jain, 2022).

Building on these insights, the present study posits a relational framework in which AI awareness and influencing factors jointly affect consumer buying behavior in the electronics sector.

Thus, the following hypothesis is formulated.

H2. AI awareness and influencing factors are significantly related to consumer buying behavior toward electronic products.

By explicitly defining and theorizing these hypotheses, the study advances existing literature by empirically examining *how AI awareness and associated influencing factors collectively shape buying behavior,* rather than treating AI adoption as a purely technological phenomenon. This hypothesis-driven approach strengthens the analytical rigor of the study and ensures alignment between theory, methodology, and empirical testing.

3. Research methodology

3.1 Research design

Guided by prior methodological frameworks in consumer behavior and AI research (Paul, 2024; Paul and Kaurav, 2025), this study adopts *a quantitative, cross-sectional research design* using a structured survey instrument. The objective is to empirically examine the relationships among AI awareness, influencing factors, and consumer buying behavior in the context of electronic product purchases.

Data were collected from 210 consumers belonging to Generation X and Generation Y residing in Mumbai, India. These cohorts were selected due to their relatively high exposure to digital platforms and AI-enabled retail environments. Data analysis was conducted using Statistical Package for the Social Sciences (SPSS) version 26 for preliminary analysis and Partial Least Squares Structural Equation Modeling (PLS-SEM) for model estimation, which is appropriate for theory development, prediction-oriented research, and complex models involving latent constructs.

3.2 Sample design

The sample comprised 210 respondents who had prior experience purchasing electronic products through online or AI-enabled platforms. Despite this, efforts were made to ensure demographic heterogeneity in terms of age, gender, education, and income, consistent with consumer behavior research in emerging markets. The participants belonged to Generation X and Generation Y.

The sample size exceeds the minimum requirements recommended for PLS-SEM analysis, satisfying both the “10-times rule” and more recent power-based guidelines.

3.3 Questionnaire design and measurement of constructs

The survey instrument comprised close-ended questions measured on a five-point Likert scale ranging from 1 (“strongly disagree”) to 5 (“strongly agree”). All measurement items were adapted from well-established and validated scales in prior studies and were contextually modified to reflect consumer interactions with AI-enabled platforms in the consumer electronics market. *AI awareness* was measured using items that captured respondents’ familiarity with the use of AI in marketing and retail environments, including awareness of recommendation systems, chatbots, and personalized advertising, drawing on scales developed by Sharma *et al.* (2024) and Meddah (2024). *Influencing factors* were operationalized as a multidimensional construct comprising perceived usefulness and perceived ease of use, adapted from the TAM (Davis, 1989), trust, adapted from Hallikainen *et al.* (2023), and personalization, adapted from Wang and Zhou (2023). *Consumer buying behavior* was assessed through items measuring purchase intention, confidence in AI-assisted decision-making, and the likelihood of using AI-enabled platforms for purchasing electronic products, based on Prakash and Singh (2023). Reliability analysis indicated satisfactory internal consistency for all constructs, with Cronbach’s alpha and composite reliability values exceeding the recommended threshold of 0.70, thereby confirming the reliability of the measurement scales.

4. Data analysis

The table shows that the demographic distribution of respondents indicates a significant gender disparity, with males (110 respondents) outnumbering females (100 respondents). Most participants fell within the age groups of 26–35 years (75 respondents) and 25 years or younger (60 respondents), indicating a younger demographic dominance, while only a small proportion were aged 60 years or older (8 respondents). Regarding educational qualifications, graduates (84 respondents) and postgraduates (64 respondents) formed the largest segments, followed by undergraduates (38 respondents) and those holding professional degrees (24 respondents). In terms of occupation, the largest group comprised individuals in private service (77 respondents), followed by those in business (44 respondents) and government service (36 respondents). Students (32 respondents) and homemakers (21 respondents) constituted a smaller proportion of the sample. This demographic profile reflects a diverse representation of educational and occupational backgrounds, predominantly comprising younger and educated individuals in professional or business roles.

As shown in Table,1 it is graphically represented in the form of a bar diagram as shown below.

After the explanation of demographic factors as given in Figure 1, it is important to understand the responses related to the variables. The following table indicates the awareness of AI applicable in the buying process of electronic products.

Using the above responses, as per Table 2, the mean score of Awareness of AI Use was obtained using the following formula:

$$\text{Mean score of Awareness of AI Use} = \frac{\text{Sum of rating of Five questions}}{\text{Maximum rating (25)}} \times 100$$

Using the above formula, mean scores were obtained for each respondent and for all 140 respondents.

Table 3 indicates that the mean score of Awareness of AI Use is 67.31%, with a standard deviation of 21.96, suggesting high variation in the responses.

After understanding the descriptive statistics of awareness, it is important to understand the influencing factors of the use of AI in the purchase decisions of electronic products.

Table 1. Demographic factors

Sr. No	Demographic factor	Category	Frequency
1	Gender	Male	110
		Female	100
2	Age Group	Up to 25 Years	60
		26–35 Years	75
		36–45 Years	43
		46–60 Years	24
		More than 60 Years	8
3	Qualification	Undergraduate	38
		Graduate	84
		Post Graduate	64
		Professional Degree	24
4	Occupation	Student	32
		Business	44
		Private Service	77
		Government Service	36
		Homemaker	21

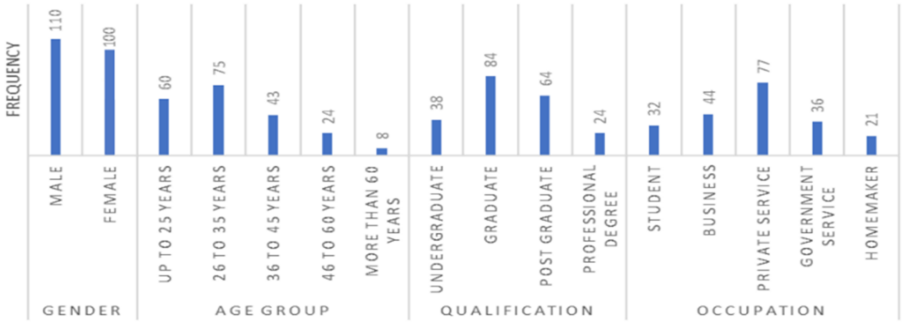


Figure 1. Demographic factors

Table 2. Awareness factors

Sr. No	Statement	Strongly disagree (1)	Disagree (2)	Neutral (3)	Agree (4)	Strongly agree (5)
5.1	I am aware that artificial intelligence is extensively used in e-commerce platforms for electronic products	34	28	30	36	82
5.2	I know that AI algorithms recommend electronic products based on my browsing and purchase history	27	28	26	50	79
5.3	I understand that AI tools influence the advertisements I see for electronic products on social media and other platforms	30	46	47	34	53
5.4	I am informed about AI-enabled features like chatbots and virtual assistants assisting in the buying process of electronic goods	19	28	40	44	79
5.5	I believe AI plays a significant role in improving my shopping experience when purchasing electronic products	36	59	41	33	41

Table 3. Descriptive statistics of awareness factors

Descriptive statistics					
	N	Minimum	Maximum	Mean	Std. deviation
Awareness of AI use	210	20	100	67.31	21.964
Valid *N* (listwise)	210				

As per Table 4, the mean score of the Influencing Factors was obtained using the following formula:

$$\text{Mean score of Influencing Factor} \frac{\text{Sum of ratings of Five questions}}{\text{Maximum rating (25)}} \times 100$$

Table 4. Influencing factor

Sr. No	Statement	Strongly disagree (1)	Disagree (2)	Neutral (3)	Agree (4)	Strongly agree (5)
6.1	I frequently rely on AI-based recommendations to explore electronic products online	74	36	49	13	38
6.2	I actively use AI tools, like price comparison platforms or review analyzers, to make decisions while purchasing electronic goods	35	52	57	37	29
6.3	I consult AI-powered customer support (e.g. chatbots or smart assistants) during the shopping process for electronic products	37	45	54	32	42
6.4	AI-driven customization of electronic product listings based on my preferences positively impacts my decision-making	57	29	46	36	42
6.5	I follow AI-generated suggestions, such as "frequently bought together," while purchasing electronic products	30	37	57	37	49

Using the above formula, mean scores were obtained for each respondent and for all 140 respondents.

Table 5 indicates that the mean score of the Influencing Factors is 57.90%, with a standard deviation of 24.51, suggesting high variation in the responses.

After understanding the descriptive statistics of the influencing factors, it is important to understand the buying behavior of the use of AI in electronic products.

As per Table 6 the mean score of Buying Behavior is obtained using the formula given below.

$$\text{Mean score of Buying Behavior} = \frac{\text{Sum of the rating of the Five questions}}{\text{Maximum rating (25)}} \times 100$$

Using the above formula mean scores are obtained for each respondent and also for all 140 respondents.

Table 7 indicates that the mean score of Buying Behavior is 57.37% with a standard deviation of 24.21, suggesting high variation in the responses.

To study the RO1, the following hypothesis is designed and presented as follows.

H1: There is a significant difference in awareness according to demographic factors.

To test the above hypothesis, ANOVA and *F*-test are applied, and the results are given in Table 8.

Table 5. Descriptive statistics of influencing factors

Descriptive statistics					
	N	Minimum	Maximum	Mean	Std. deviation
Influencing factor	210	20	100	57.90	24.518
Valid *N* (listwise)	210				

Table 6. Buying behavior factors

Sr. No	Statement	Strongly disagree (1)	Disagree (2)	Neutral (3)	Agree (4)	Strongly agree (5)
7.1	AI recommendations make it easier for me to find the products I am interested in	73	40	47	13	37
7.2	I trust AI-powered product suggestions more than traditional recommendations from human salespeople	34	57	51	41	27
7.3	AI-driven personalized marketing (e.g. discounts, offers) makes me more likely to make a purchase	34	49	51	36	40
7.4	I feel that AI systems consider my preferences accurately when suggesting products	56	38	40	36	40
7.5	I am concerned about the privacy of my personal data when AI is used to personalize my shopping experience	30	44	54	34	48

Table 7. Descriptive statistics of buying behavior

Descriptive statistics	*N*	Minimum	Maximum	Mean	Std. deviation
Buying behavior	210	20	100	57.37	24.117
Valid *N* (listwise)	210				

Table 8. Results of ANOVA and *F*-test

Demographic factor	Test	*p*-value	Results
Gender	*T*-test	0.374	Rejected
Age	ANOVA and *F*-test	0.000	Accepted
Qualification	ANOVA and *F*-test	0.000	Accepted
Occupation	ANOVA and *F*-test	0.001	Accepted

Interpretation: As per Table 8, the results indicate that the calculated *p*-value for gender is more than 0.05. Hence Null hypothesis is accepted and the alternative hypothesis is rejected. For *age ($p = 0.000$), qualification ($p = 0.000$), and occupation ($p = 0.001$)*, the *p*-values are *less than 0.05*, which supports rejection of the null hypothesis and acceptance of the alternative hypothesis, indicating significant differences in awareness across these demographic factors.

Results: To understand the findings, mean scores are obtained, and the results are given in Table 9.

The data on awareness of AI in purchasing electronic products highlights notable differences across various demographic factors. In terms of gender, males have a higher mean score (68.16) than females (65.15), suggesting that males may have slightly greater awareness or engagement with AI technologies. Age-wise, individuals in the 36–45 years group exhibit the highest mean score (70.88), followed by those in the 26–35 years group (69.28), while individuals in the 46–60 years age group show a significantly lower mean score (47.83). This

Table 9. Awareness according to demographic factors

Demographic factor	Category	Mean	Std. dev
Gender	Male	68.16	21.014
	Female	65.15	24.286
Age Group	Up to 25 Years	70.47	24.393
	26–35 Years	69.28	19.991
	36–45 Years	70.88	20.196
	46–60 Years	47.83	16.322
	More than 60 Years	64.50	18.071
Qualification	Undergraduate	56.32	19.383
	Graduate	69.43	21.791
	Post Graduate	64.31	21.110
	Professional Degree	85.33	16.287
Occupation	Student	56.32	19.383
	Business	69.43	21.791
	Private Service	64.31	21.110
	Government Service	85.33	16.287
	Homemaker	79.00	14.585

suggests that awareness of AI in purchasing electronic products decreases with age, with younger individuals being more familiar with AI-driven technologies. Regarding education, individuals with a professional degree have the highest awareness (85.33), likely due to greater exposure to advanced technologies, whereas those with an undergraduate qualification have the lowest awareness (56.32). In terms of occupation, government service employees and homemakers show the highest mean scores (85.33 and 79.00, respectively) (see Figure 2), which may reflect a greater use of AI tools for convenience and decision-making. Conversely, students and individuals in private service or business have lower awareness scores, potentially due to less exposure or focus on AI in their daily activities. Overall, the data reveals that higher education, age, and occupation significantly influence awareness of AI in purchasing electronic products, with younger, more educated, and professionally engaged individuals demonstrating higher awareness levels.

Findings: There is a significant difference in awareness according to demographic factor.

To study the RO2, following hypothesis is designed and presented as follows.

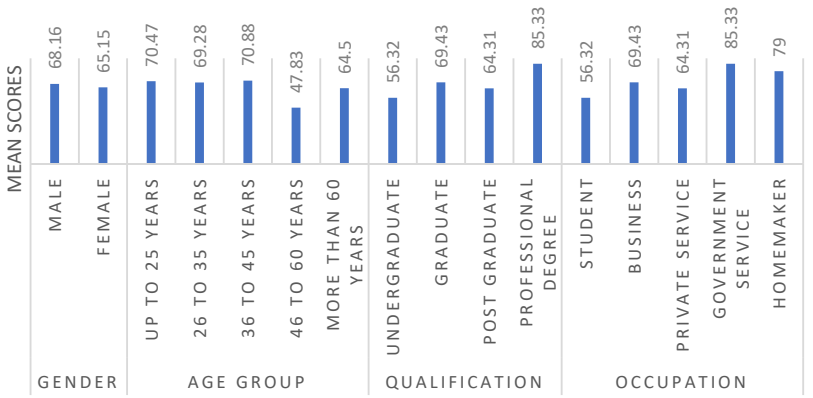


Figure 2. Awareness according to demographic factors

H2: There is a relationship between awareness, influencing factors and buying behavior.

To test the above hypothesis, the Pearson correlation test is applied and the results are reflected in Table 10.

Interpretation: As per Table 10 the results indicate that the calculated *p*-value is 0.000. It is less than 0.05. Therefore, the Pearson Correlation test is rejected. Hence Null hypothesis is rejected and the Alternate hypothesis is accepted.

Results: The Pearson correlation results indicate a significant relationship between buying behavior, awareness of AI use, and influencing factors in consumer decision-making. The correlation between buying behavior and awareness of AI use is positive and moderate (0.242**), with a significance level of 0.001, suggesting that as awareness of AI use increases, so does the likelihood of certain buying behaviors. The correlation between buying behavior and influencing factors is extremely strong (0.978**), with a significance level of 0.000, indicating that influencing factors (such as AI-driven recommendations, personalized experiences, etc.) have a very significant impact on consumer buying behavior. These findings highlight the critical role of both AI awareness and external influencing factors in shaping consumer purchasing decisions.

Findings: There is a relationship between awareness, influencing factors, and buying behavior.

4.1 Objective of Structural Equation Model (SEM)

The objective of SEM is to evaluate how each question impacts on the underlying factors, thereby affecting consumer buying behavior.

Linear regression:

Dependent variable: Buying Behavior.

Independent variable: IF, Awareness of AI Use IF, Awareness of AI Use.

In this context (Table 11), the *R* square value of 0.957 indicates that approximately 95.7% of the variance in the dependent variable, buying behavior, can be explained by the independent variables: IF and Awareness of AI Use. This means that the model is highly effective in predicting buying behavior based on these factors, with a strong relationship between the independent and dependent variables. The remaining 5.0% of the variance in buying behavior is attributed to other factors not included in the model. The high R Square value suggests that the chosen predictors are highly relevant and explain most of the observed variations in consumer purchasing behavior.

The results in Table 12 indicate that the *p*-value is 0.000. It is less than 0.05. It indicates that the linear regression model is a good to fit.

The mathematical equation to estimate the Buying Behavior factors is presented as follows:

Table 10. Correlations test

		Buying behavior	Awareness of AI use	Influencing factor
Buying behavior	Pearson Correlation	1	0.242**	0.978**
	p-value		0.000	0.000
	N	210	210	210
Awareness of AI use	Pearson Correlation	0.242**	1	0.232**
	p-value	0.000		0.001
	N	210	210	210
Influencing factor	Pearson Correlation	0.978**	0.232**	1
	p-value	0.000	0.001	
	N	210	210	210

Note(s): **. Correlation is significant at the 0.01 level (2-tailed)

Table 11. Model summary

Model	*R*	*R*-square	Adjusted *R*-square	Std. error of the estimate
1	0.978[a]	0.957	0.956	5.043

Note(s): [a]Predictors: (Constant), Influencing Factor, Awareness of AI Use

Table 12. ANOVA test

Model		Sum of squares	Df	Mean square	F	*p*-value
1	Regression	116292.853	2	58146.426	2286.457	0.000
	Residual	5264.176	207	25.431		
	Total	121557.029	209			

$$\mathrm{BB} = 0.683 + 0.018 * \mathrm{A} + 0.958 * \mathrm{IF}$$

The above regression equation (see Table 13) is useful for estimating the Buying Behavior of respondents selected randomly.

4.2 Structural equational modelling

SEM is a statistical technique used to analyze complex relationships among observed and latent variables. In the provided diagram, SEM is applied to explore the relationships between three constructs: Awareness, Influencing Factors, and Buying Behavior. The latent variables (depicted as blue circles) are measured using multiple observed indicators (yellow rectangles), such as A-1 to A-5, IF-1 to IF-5, and BB-1 to BB-5. SEM is particularly valuable for identifying key drivers and understanding the direct and indirect effects between variables in a comprehensive model (see Figure 3).

The path coefficients in the SEM model indicate the strength and significance of the relationships between the constructs. In this model, the path coefficient between Awareness and Buying Behavior is 0.025, indicating a weak, negligible direct influence of awareness on buying behavior (see Table 14). This indicates that awareness alone may not significantly drive purchasing decisions. Conversely, the path coefficient between the IF and Buying Behavior is 0.968, indicating a very strong and direct impact. This suggests that factors such as price,

Table 13. Coefficients

Model		Unstandardized coefficients		Standardized coefficients		
		B	Std. error	Beta	*t*	Sig.
1	(Constant)	0.683	1.271		0.538	0.591
	Awareness of AI use (A)	0.018	0.016	0.016	1.092	0.276
	Influencing factor (IF)	0.958	0.015	0.974	65.514	0.000

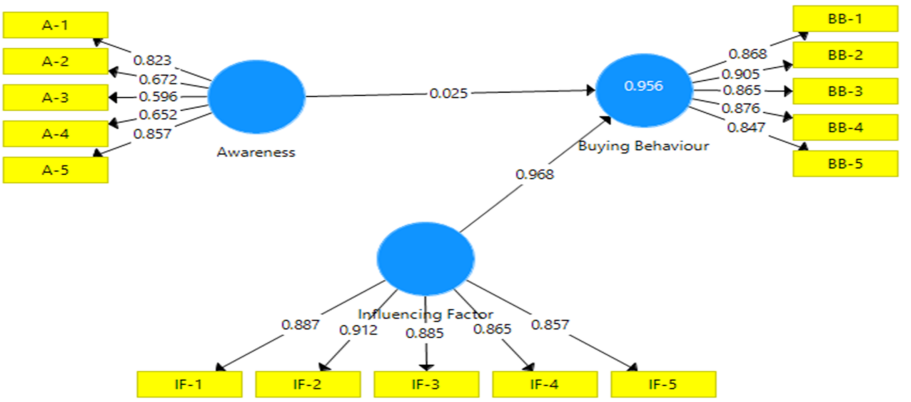


Figure 3. Structural equation model (SEM)

Table 14. Path coefficients

	Buying behavior
Awareness	0.025
Influencing factor	0.968

quality, brand reputation, or other influencing elements play a dominant role in shaping consumer buying behavior, overshadowing the effect of mere awareness.

The outer loadings represent the strength of the relationship between each observed variable (indicator) and its corresponding latent construct. For Awareness, the indicators (A-1 to A-5) have loadings ranging from 0.596 to 0.857, indicating a moderate to strong representation of the construct. For Buying Behavior, the loadings for indicators (BB-1 to BB-5) range from 0.847 to 0.905, reflecting strong representation. Similarly, for the IF, the indicators (IF-1 to IF-5) have high loading between 0.857 and 0.912, indicating strong reliability (see Table 15). These loadings validate that the observed variables effectively measure their respective latent constructs in the model.

The outer weights indicate the relative importance of each observed variable (indicator) in forming its respective latent construct. For Awareness, A-5 has the highest weight (0.586), highlighting its strong contribution, while A-3 (0.078) has the least impact. For Buying Behavior, the weights for all indicators (BB-1 to BB-5) are relatively similar, ranging from 0.223 to 0.235, indicating that all indicators contribute almost equally to the construct. Similarly, for the IF, the weights of IF-1 to IF-5 range narrowly from 0.221 to 0.234, showing a balanced influence of all indicators on the construct (see Table 16). These weights emphasize the significance of specific indicators in shaping their respective latent variables within the model.

5. Discussion

The SEM analysis reveals insightful dynamics among the constructs of Awareness, Influencing Factors, and Buying Behavior. The path coefficient results demonstrate that while Awareness has a negligible direct effect (0.025) on Buying Behavior, Influencing Factors exert a dominant and highly significant impact (0.968), underscoring that consumer

Table 15. Outer loadings

	Awareness	Buying behavior	Influencing factor
A-1	0.823		
A-2	0.672		
A-3	0.596		
A-4	0.652		
A-5	0.857		
BB-1		0.868	
BB-2		0.905	
BB-3		0.865	
BB-4		0.876	
BB-5		0.847	
IF-1			0.887
IF-2			0.912
IF-3			0.885
IF-4			0.865
IF-5			0.857

Table 16. Outer weights

	Awareness	Buying behavior	Influencing factor
A-1	0.371		
A-2	0.123		
A-3	0.078		
A-4	0.098		
A-5	0.586		
BB-1		0.232	
BB-2		0.235	
BB-3		0.225	
BB-4		0.231	
BB-5		0.223	
IF-1			0.228
IF-2			0.234
IF-3			0.227
IF-4			0.221
IF-5			0.223

decisions are driven more by practical considerations like price, quality, and brand image rather than mere awareness. This aligns with the outer weights, where the indicator A-5 contributes the most to Awareness, but its overall effect remains limited. The consistently high outer loadings across all constructs affirm the reliability of the indicators in measuring their respective latent variables. Additionally, the balanced distribution of outer weights among Buying Behavior and IF indicators suggests a well-structured model with uniformly strong measurement items. Overall, the findings emphasize that while awareness is necessary, it is the strength and relevance of influencing factors that decisively shape consumer purchasing behavior. The findings indicate that age, higher education, and occupation significantly affect AI awareness in electronic product purchases, with younger, well-educated, and professionally active individuals showing greater awareness. A strong correlation (0.978) at a significance level of 0.000 confirms that influencing factors—like AI-driven recommendations and personalized experiences—have a very significant impact on

consumer buying behavior. These results emphasize the crucial role of both AI awareness and external influences in shaping purchase decisions.

5.1 Theoretical contribution

This study advances the theoretical understanding of consumer behavior by emphasizing the importance of AI awareness and demographic influences as key drivers of electronic product decision-making. The intersection of awareness with demographic factors offers a defined framework for further studies that can explore AI'srole in shaping consumer decision-making. The study's findings indicate that AI awareness is not uniformly distributed, and its impact on purchasing decisions varies significantly across demographic segments. This supports theoretical models that highlight the mediating role of digital competence in technology adoption and consumer trust in AI systems (Nasir *et al.*, 2024). By uncovering the intersection between awareness and demographics, this study offers a structured conceptual foundation for future inquiries into how AI-based interventions can be personalized based on consumer profiles. Furthermore, the framework extends the TAM and the Unified Theory of Acceptance and Use of Technology (UTAUT) by incorporating AI-specific awareness and behavioral intentions into consumer behavior theories. This reflects recent trends in consumer research that call for the integration of AI-related cognitive factors into existing behavioral models (Srivastava and Kapoor, 2022).

5.2 Limitations

This study had four limitations. First, data were collected only from Mumbai, which limits generalizability; future studies should include multiple cities and regions. Second, the use of non-probability sampling reduces representativeness, which could be addressed by probability sampling. Third, self-reported data may involve bias; thus, combining survey responses with behavioral or transactional data is recommended. Finally, the cross-sectional design limits causal inference; longitudinal or experimental designs can better capture changes in consumer behavior over time.

5.3 Managerial implications

This study emphasizes the importance of electronics stores integrating AI not only as a support tool but also for consumer-facing intervention. Marketing to this particular target group with appropriate product education can enhance customer engagement, especially because young and professionally qualified consumers are more aware of AI. Brands can influence consumers' purchasing decisions by utilizing data-driven insights, intelligent recommendations, and AI-driven customization to deliver personalized experiences to consumers. Managers should develop AI-based personalization strategies, such as adaptive product suggestions and dynamic pricing, to cater to individual preferences and enhance satisfaction. Additionally, transparent communication regarding the ethical use of AI, including data privacy and fairness, can build consumer confidence and foster long-term trust. By aligning AI initiatives with demographic preferences and maintaining ethical transparency, businesses can strengthen customer loyalty and brand reputation.

6. Conclusion

This study established a significant relationship between AI awareness, influencing factors, and consumer buying behavior for electronic products. The findings indicate that demographic variables, particularly age, educational qualifications, and occupation—play a critical role in shaping AI awareness, with younger, professionally active, and well-educated consumers exhibiting higher levels of familiarity with AI applications.

Pearson's correlation analysis confirmed a strong association between buying behavior, influencing factors, and AI awareness, while linear regression further validated that

influencing factors, such as AI-driven recommendations and personalized experiences, are key predictors of consumer purchase decisions. SEM analysis reinforced these results, revealing that influencing factors exert the most substantial impact on buying behavior.

Moreover, supporting evidence from the existing literature highlights the pivotal role of AI-enabled tools in influencing online consumer behavior, especially in the technology and electronics sectors. Overall, this study emphasizes the dual importance of enhancing AI awareness and strategically leveraging influencing factors to effectively shape consumer decisions. These insights suggest that marketers and retailers must not only educate consumers about AI-driven solutions but also strengthen AI-powered touchpoints throughout the customer journey.

While this study focused on AI'sinfluence of AI on consumer buying behavior in the electronics sector, future research could broaden the scope to include other industries, such as retail, healthcare, and financial services, where AI-driven personalization and automation are rapidly evolving. Additionally, longitudinal studies could provide deeper insights into how consumer attitudes toward AI change over time, especially as technology adoption matures. Incorporating cross-cultural or cross-generational analyses would also enhance our understanding of how demographic and contextual differences shape AI acceptance and trust across sectors.

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