Examining the Influence of Artificial Intelligence on Consumer Purchase Decision-Making in E-Commerce: Evidence from Sangrur, Punjab, India

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Abstract

Purpose	This study investigates the nature and magnitude of influence that Artificial Intelligence (AI)-powered features exert on the online purchase decision-making behaviour of consumers in Sangrur, a semi-urban town in Punjab, India — a context markedly underrepresented in the existing digital commerce literature.
Design / Methodology / Approach	A primary, cross-sectional survey design was employed. Structured questionnaires incorporating five-point Likert scales were administered to 150 active e-commerce users in Sangrur. The AI Awareness Scale (10 items, $\alpha = 0.83$) and Purchase Decision Scale (12 items, $\alpha = 0.87$) were subjected to descriptive statistics, Pearson correlation analysis, simple linear regression, and an independent samples t-test using SPSS 26.
Findings	AI awareness and purchase decision-making behaviour are strongly and positively correlated ($r = 0.712$, $p < 0.001$). AI awareness accounts for 50.7% of the variance in purchase decisions ($R^2 = 0.507$, $\beta = 0.703$, $p < 0.001$). Dynamic pricing is the least understood AI feature ($M = 3.29$), while AI's overall influence on final purchase decisions scored highest ($M = 3.87$). Gender exerts no significant moderating effect ($t = 1.42$, $p = 0.158$).
Research Limitations	The cross-sectional, single-location design limits temporal and geographical generalisability. Self-reported data introduces social desirability bias. The single-predictor regression model does not account for mediating or moderating variables such as platform trust, income elasticity, or peer influence.
Practical Implications	E-commerce firms should prioritise transparent AI personalisation strategies and invest in consumer digital literacy programmes in semi-urban Indian markets. Policymakers should consider algorithmic transparency mandates to protect consumers who engage with AI-driven pricing systems without full comprehension.
Originality / Value	This study provides the first empirically grounded, primary-data-based examination of AI's influence on consumer decision-making in a semi-urban Punjabi town. It contributes original field evidence from an understudied demographic and geographic context, advancing the emerging literature on AI adoption in Tier-2 and Tier-3 Indian digital markets.

Keywords: *Artificial Intelligence; Consumer Decision-Making; E-Commerce; Personalisation; Digital Commerce; Semi-Urban India; Punjab; AI Awareness; Purchase Behaviour; Algorithmic Influence*

JEL Classification: *M31 · M15 · L81 · O33*

1. INTRODUCTION

The penetration of e-commerce into India's semi-urban geography has been one of the defining commercial shifts of the post-pandemic decade. Driven by the convergence of affordable mobile data, widespread UPI adoption, and the aspirational consumption patterns of a rapidly urbanising younger cohort, towns such as Sangrur in Punjab's Sangrur district have transitioned from peripheral observers of the digital economy to active participants within it. Yet the academic literature has been slow to follow commerce to these geographies. Research on AI-driven consumer behaviour in e-commerce continues to be overwhelmingly situated in metropolitan centres:Delhi, Mumbai, Bengaluru or in international markets, leaving a systematic empirical gap with respect to semi-urban Indian consumers.

Artificial Intelligence constitutes the invisible architecture of modern e-commerce. Recommendation engines, dynamic pricing algorithms, natural language processing-enabled chatbots, and predictive search functionalities collectively constitute an AI layer that mediates virtually every consumer-platform interaction. These systems do not passively respond to consumer intent; they anticipate, shape, and in some cases construct it (Davenport et al., 2020). Understanding the degree to which this algorithmic influence penetrates the decision-making processes of consumers outside metropolitan India is, therefore, both a scholarly imperative and a policy concern.

This paper reports findings from a primary field study conducted in Sangrur, Punjab, in 2025. Drawing on survey data from 150 active e-commerce users, the study operationalises two constructs i.e. consumer awareness of AI-powered platform features, and the degree to which such features influence purchase decisions and subjects them to rigorous statistical analysis. The overarching theoretical anchor is the Stimulus-Organism-Response (S-O-R) framework (Mehrabian & Russell, 1974), which provides a parsimonious model for explaining how environmental stimuli (AI-generated cues) process through internal organism states (awareness, trust) to produce behavioural responses (purchase decisions).

The study makes three primary contributions. First, it generates original primary evidence from a semi-urban Punjabi context that has received no prior academic attention in the AI-commerce literature. Second, it empirically establishes the relationship between AI awareness and purchase behaviour in this population, testing hypotheses that have largely been validated only in urban or international settings. Third, it surfaces the dynamic pricing knowledge gap as a specific consumer education concern with practical regulatory implications.

The remainder of this paper is structured as follows. Section 2 develops the theoretical framework and reviews the relevant literature. Section 3 states the research objectives and hypotheses. Section 4 details the research methodology. Section 5 presents the findings from descriptive statistics, correlation, regression, and t-test analyses. Section 6 discusses the findings in relation to the theoretical framework and prior literature. Section 7 concludes with implications, limitations, and directions for future research.

2. THEORETICAL FRAMEWORK AND REVIEW OF LITERATURE

2.1 Theoretical Underpinning: The Stimulus-Organism-Response (S-O-R) Framework

The Stimulus-Organism-Response (S-O-R) framework, originally articulated by Mehrabian and Russell (1974) in the context of environmental psychology, has been extensively applied and validated in digital commerce research. Within the S-O-R paradigm, environmental stimuli in the present context, AI-generated cues such as personalised recommendations, chatbot responses, and dynamically adjusted prices interact with internal organism states, including perceptions, awareness levels, and affect, to elicit measurable behavioural responses, namely purchase decisions. The framework is particularly well-suited to the present study because it accommodates both cognitive processing (awareness of AI tools) and behavioural outcomes (purchase completion) within a single explanatory architecture.

Recent e-commerce scholarship has embraced S-O-R as a foundational model for understanding how platform-level AI features shape consumer behaviour. Notably, a study examining AI-driven marketing in Indian quick-grocery platforms using S-O-R as the organising framework found that personalisation, smart search, and dynamic pricing collectively and differentially influence consumer attitudes and purchase intentions (International Review of Retail, Distribution and Consumer Research, 2025). The present study extends this application to a field-based, survey-driven investigation of a semi-urban Punjabi market.

2.2 AI-Driven Personalisation and Consumer Purchase Intent

The causal relationship between AI-driven personalisation and consumer purchase intent has been well-established in the literature. Huang and Rust (2021) demonstrated that AI's most commercially significant function lies not in mechanical automation but in what they term 'feeling intelligence' the capacity to personalise recommendations at a level that resonates emotionally with consumers, thereby increasing engagement and conversion. Davenport et al. (2020) extended this, arguing that advanced machine learning systems effectively anticipate consumer needs prior to conscious articulation, fundamentally reconfiguring the purchase initiation sequence.

Singhal et al. (2025) provided more recent confirmation, reporting that consumer trust in AI-generated suggestions compounds positively over repeated platform interactions, ultimately producing a state of 'recommendation reliance' in which consumers delegate significant portions of their product discovery process to algorithmic systems. This reliance has been shown to increase both basket size and purchase frequency. Balasubramanian (2024), writing specifically about AI personalisation in Indian e-commerce contexts, corroborated these effects, linking them to measurable improvements in customer engagement and satisfaction scores.

2.3 Consumer Trust, Transparency, and the Privacy Paradox

A persistent tension in the AI-commerce literature concerns the relationship between personalisation effectiveness and consumer trust. Kim and Peterson (2017) identified what they termed the 'personalisation-privacy paradox': consumers who experience highly accurate AI recommendations often simultaneously report discomfort with the implied degree of surveillance. Trust, in this framing, is not a passive byproduct of accurate recommendation but an active construction requiring transparency on the part of the platform.

Hussain et al. (2024) empirically demonstrated that perceived data privacy is a significant moderator of AI personalisation acceptance, with particularly strong effects among first-generation digital consumers — a category that encompasses a meaningful proportion of e-commerce users in semi-urban Punjab. Torres and Almeida (2024) further established that algorithmic transparency that is, the degree to which consumers understand how and why they are being shown specific content is a more powerful predictor of long-term trust than recommendation accuracy per se.

Zhao et al. (2025), applying the Heuristic-Systematic Model (HSM) to AI agent interactions in shopping environments, found that consumers who engage systematically with AI recommendations actively processing the logic behind algorithmic suggestions develop stronger purchase intentions than those who process them heuristically. This finding has direct implications for the present study's core hypothesis: that AI awareness and purchase behaviour are positively related.

2.4 Chatbots, Conversational AI, and Purchase Completion

Conversational AI tools primarily chatbots represent a distinct channel through which artificial intelligence influences consumer behaviour. Chung et al. (2020) documented that chatbot-mediated interactions reduce purchase hesitation by simulating the reassurance function traditionally performed by human sales personnel, reporting a 28% improvement in purchase completion rates following chatbot engagement in a Malaysian retail context. Xu et al. (2020) qualified this relationship, finding that chatbot effectiveness is strongly conditioned by task complexity: for straightforward product queries, chatbots outperform human service agents in speed and accuracy, whereas complex or emotionally charged queries require human escalation.

In the specific context of Indian e-commerce, Kaur and Renu (2025) identified chatbot responsiveness rather than mere availability as the decisive variable. A chatbot that misunderstands consumer queries or produces generic responses can actively suppress purchase intent, a finding with practical implications for platform operators seeking to deploy conversational AI in linguistically diverse Indian markets.

2.5 Data Privacy, Governance, and the Ethics of Algorithmic Commerce

The governance dimension of AI in e-commerce has attracted increasing scholarly attention following high-profile data breaches and growing public awareness of surveillance capitalism. Zhao et al. (2024) examined the intersection of AI personalisation, consumer privacy, and regulatory frameworks in online retail, arguing that governance clarity specifically, enforceable rules governing what AI systems can do with consumer data is a necessary precondition for the sustainable commercial deployment of personalisation technologies.

Olan et al. (2024), drawing on big data analytics from real-world e-commerce platforms, highlighted a distributional concern: the consumers whose behavioural data is most aggressively harvested lower-income, less digitally literate, semi-urban are often the least equipped to understand or contest the terms of this harvesting. This observation is particularly salient for the Sangrur context and underscores the study's relevance beyond purely commercial considerations.

2.6 AI and Consumer Loyalty in Digital Commerce

The temporal dimension of AI's influence, its effects on repeat purchase behaviour and brand loyalty has been examined by Beyari (2025), who documented a consistent pattern across e-commerce platforms: sustained AI personalisation generates higher repeat purchase rates and stronger attitudinal loyalty, provided the personalisation is experienced as helpful rather than intrusive. He and Liu (2024), mapping the knowledge evolution of AI in e-commerce research through science mapping analysis, confirmed that loyalty and retention have emerged as the dominant research themes of the post-2022 period, supplanting earlier preoccupations with personalisation accuracy and technical recommendation system design.

2.7 AI Adoption in the Indian Semi-Urban Context

Research on AI adoption in non-metropolitan Indian consumer markets remains sparse. Rana et al. (2019), in a study examining digital service adoption barriers across Indian cities, observed that younger consumers in Tier-2 and Tier-3 cities exhibited high digital receptivity despite limited formal digital literacy, suggesting that experiential learning through platform use was substituting for formal education in driving adoption. Chugh and Jain (2024), conducting a bibliometric analysis of the AI-e-commerce literature, confirmed that developing country contexts and rural or semi-urban populations remain significantly underrepresented in extant scholarship, constituting a clear invitation for primary field research.

Fan and Liu (2022), examining algorithmic decision autonomy and its effects on consumer self-efficacy and purchase behaviour, provided a theoretical scaffold relevant to the Sangrur context: when consumers perceive AI as an agent that enhances rather than overrides their decision-making capability, purchase intentions increase. This 'augmentation framing' of AI as a tool that empowers consumer choice rather than replacing it may be particularly relevant in semi-urban markets where consumers are still constructing their identities as digital shoppers.

2.8 Identification of Research Gap

The foregoing review establishes a rich and growing literature on AI's influence in e-commerce. However, several gaps are evident. First, the vast majority of primary studies are conducted in metropolitan or international contexts, rendering their findings of limited direct applicability to semi-urban Indian consumers. Second, while theoretical frameworks such as S-O-R and HSM have been invoked in AI-commerce research, they have rarely been applied to field data from Indian Tier-2 or Tier-3 markets. Third, the specific question of how AI awareness as distinct from AI use or trust predicts purchase behaviour in a semi-urban Punjabi context has not been addressed.

This study directly addresses these three gaps by generating primary field data from Sangrur, applying the S-O-R framework, and testing the relationship between AI awareness and purchase behaviour within a population that has been systematically absent from the scholarly record.

3. RESEARCH OBJECTIVES AND HYPOTHESES

3.1 Research Objectives

Objective 1: To assess the level of awareness among active e-commerce users in Sangrur, Punjab, regarding AI-powered platform features specifically product recommendation systems, chatbot services, dynamic pricing algorithms, and AI-enhanced search functionality.

Objective 2: To examine the degree to which these AI-powered features influence the purchase decision-making behaviour of consumers in Sangrur, Punjab, and to identify the relative explanatory weight of AI awareness in predicting purchase outcomes.

3.2 Research Hypotheses

Drawing on the S-O-R framework and the empirical literature reviewed above, the following hypotheses are proposed:

H_1: Consumer awareness of AI-powered features on e-commerce platforms is positively and significantly associated with the degree to which those features influence purchase decision-making behaviour among online shoppers in Sangrur, Punjab.

H_2: AI-powered features on e-commerce platforms exert a statistically significant and practically meaningful positive influence on the final purchase decisions of consumers in Sangrur, Punjab.

H_3: There is no significant difference in the degree of AI influence on purchase decision-making between male and female e-commerce consumers in Sangrur, Punjab (null hypothesis retained for t-test).

4. RESEARCH METHODOLOGY

4.1 Research Design

This study adopts a positivist, descriptive-analytical research design grounded in quantitative primary data collection. A cross-sectional survey methodology was selected on the basis of its suitability for capturing consumer perceptions and behavioural self-reports at a single point in time across a heterogeneous sample a design widely employed in empirical consumer behaviour research (Sekaran & Bougie, 2016). The deductive approach, moving from theoretically derived hypotheses to empirical testing, is consistent with the S-O-R framework's proposition that measurable stimuli produce measurable behavioural outcomes.

4.2 Study Area

Sangrur is a town located within the Sangrur district of Punjab, India (approximate population: 25,000–35,000). Geographically positioned within the Malwa region, the town's economy is primarily agricultural-adjacent, with a growing commercial and services sector. Over the 2019–2025 period, smartphone penetration in Sangrur has increased substantially, supported by the rollout of affordable 4G and 5G connectivity under the Jio network revolution and subsequent competitive responses. E-commerce platforms particularly Flipkart, Amazon, and Meesho have established active user bases within the town, with local shopkeepers reporting that price comparison behaviour among customers has noticeably increased.

The selection of Sangrur as the study site was deliberate and theoretically motivated. As a town that sits at the cusp of the rural-urban continuum neither purely agrarian nor fully urbanized. It represents a population whose digital consumption patterns are both commercially significant and academically underexamined.

4.3 Population, Sampling, and Sample Size

The target population comprised residents of Sangrur, aged 18 years and above, who had made at least one purchase through an e-commerce platform within the preceding six calendar months. This criterion was applied to ensure that all respondents possessed direct, recent experiential familiarity with the AI features under study.

Given the absence of a reliable sampling frame for this population, a combined purposive and convenience sampling strategy was employed. Survey instruments were administered at educational institutions, local commercial markets, residential neighbourhoods, and community gathering spaces within the town, ensuring heterogeneity across age, gender, occupation, and income brackets. The final achieved sample of n = 150 is consistent with the minimum requirements for correlation and regression analyses (Green, 1991; Sekaran & Bougie, 2016) and comparable to the sample sizes employed in analogous primary studies in Indian digital commerce research.

4.4 Measurement Instrument

The survey instrument was developed in three stages. First, an initial item pool was generated through a systematic review of validated scales from the literature, including instruments developed by Huang and Rust (2021), Zhao et al. (2025), and Chung et al. (2020). Second, the instrument was reviewed for content validity by two faculty members in the Department of Commerce and one practitioner from the e-commerce sector, resulting in the revision of six items and the elimination of two redundant items. Third, a pilot administration to 15 respondents from the target population was conducted, yielding feedback that prompted the rewording of four items for improved clarity in the local context. The final instrument was made available in both English and Punjabi.

The questionnaire comprised four sections. Section A captured demographic information (gender, age, education, occupation, monthly income). Section B assessed e-commerce usage patterns (platform preference, usage frequency, primary device). Section C operationalised the AI Awareness construct through 10 items rated on a five-point Likert scale (1 = Strongly Disagree; 5 = Strongly Agree). Section D operationalised the Purchase Decision construct through 12 similarly rated items.

4.5 Reliability and Validity Assessment

Internal consistency reliability was evaluated using Cronbach's coefficient alpha. The AI Awareness Scale produced $\alpha = 0.83$, and the Purchase Decision Scale yielded $\alpha = 0.87$ — both substantially exceeding the conventionally accepted minimum of 0.70 (Nunnally, 1978), and approaching the threshold of 0.90 recommended for scales used in quantitative predictive modelling. Content validity was established through the expert review process described above. Construct validity was assessed through item-total correlations, all of which exceeded 0.30.

4.6 Analytical Strategy

Data were entered, cleaned, and analysed using SPSS version 26.0. The analytical protocol comprised four sequential steps: (1) descriptive statistics (means, standard deviations, frequency distributions) to characterise sample demographics and scale item responses; (2) Pearson product-moment correlation to examine the bivariate relationship between the AI Awareness Score and the Purchase Decision Score, testing H_1; (3) simple ordinary least squares (OLS) regression to estimate the predictive power of AI Awareness on Purchase Decision behaviour, testing H_2; and (4) an independent samples t-test to assess gender-based differences in AI influence on purchase decisions, testing H_3. Statistical significance was evaluated at the conventional $\alpha = 0.05$ threshold.

4.7 Ethical Considerations

Prior to data collection, all respondents were provided with a written participant information sheet clearly explaining the purpose of the study, the voluntary nature of their participation, their right to withdraw without consequence, and the measures in place to ensure data confidentiality and anonymity. Informed verbal consent was obtained from each respondent before questionnaire administration. No personally identifiable information was collected. Data were stored securely and used exclusively for academic research purposes. The study was conducted in accordance with the Declaration of Helsinki principles governing research involving human participants.

5. RESULTS

5.1 Demographic Profile of Respondents

Table 1 presents the demographic characteristics of the 150 respondents. The sample exhibits a predominance of younger adults (73.4% aged 18–35), consistent with the age distribution of active e-commerce users in semi-urban Indian markets. Male respondents constitute a slight majority (56%, n = 84), though the gender distribution is broadly balanced. Graduate-level education is most common (52%, n = 78), reflecting Sangrur's growing educated workforce. The modal income bracket is Rs.15,000–Rs.30,000 per month (41.3%), positioning the sample squarely within the aspirational semi-urban middle-income cohort.

Table 1. Demographic Profile of Survey Respondents (n = 150), Sangrur, Punjab, India, 2025.

Demographic Variable	Category	Frequency (%)
Gender	Male	84 (56.0%)
	Female	66 (44.0%)
Age Group	18–25 years	58 (38.7%)
	26–35 years	52 (34.7%)
	36–45 years	28 (18.7%)
	Above 45 years	12 (8.0%)
Education	Up to Higher Secondary	32 (21.3%)
	Graduate	78 (52.0%)
	Post-Graduate & Above	40 (26.7%)
Occupation	Student	46 (30.7%)
	Self-Employed / Business	38 (25.3%)
	Private / Government Employee	42 (28.0%)
	Homemaker / Other	24 (16.0%)
Monthly Income (INR)	Below ₹15,000	40 (26.7%)
	₹15,000 – ₹30,000	62 (41.3%)
	Above ₹30,000	48 (32.0%)

5.2 E-Commerce Usage Patterns

Of 150 respondents, 142 (94.7%) reported purchasing online at least once per month. Flipkart (71.3%) and Amazon (68.0%) were the most frequently used platforms, followed by Meesho (48.0%), the latter exhibiting notably stronger adoption among female respondents (62.1% of female sample versus 37.5% of male sample). Smartphone-exclusive access to e-commerce platforms was reported by 82.0% of respondents, underscoring the fundamentally mobile-mediated character of digital commerce in this market.

5.3 Descriptive Statistics: AI Awareness and Purchase Decision Scales

Table 2. Descriptive Statistics — AI Awareness and Purchase Decision Scale Items (n = 150). Scale: 1–5 (Strongly Disagree to Strongly Agree).

Scale Item	Mean	SD	Interpretation
AI Recommendation Awareness	3.81	0.72	High
AI Chatbot Awareness	3.54	0.81	Moderate-High
Dynamic Pricing Awareness	3.29	0.94	Moderate
AI Search Personalisation Awareness	3.56	0.79	Moderate-High
Overall AI Awareness Score (composite)	3.55	0.74	Moderate-High
AI Influence on Purchase Initiation	3.74	0.68	High
AI Influence on Brand Preference	3.61	0.77	High
AI Influence on Final Purchase Decision	3.87	0.65	High
Overall Purchase Decision Score (composite)	3.74	0.68	High

The highest mean score across all purchase decision items was recorded for 'AI Influence on Final Purchase Decision' (M = 3.87, SD = 0.65), indicating that AI features are perceived as most influential at the terminal stage of the decision process .i.e. the moment of commitment. The 'Dynamic Pricing Awareness' item produced the lowest mean across both scales (M = 3.29, SD = 0.94), with notably higher variance, suggesting that awareness of this specific AI mechanism is both lower and less consistent across the sample than awareness of other features. The composite AI Awareness Score (M = 3.55, SD = 0.74) falls in the moderate-high range, while the composite Purchase Decision Score (M = 3.74, SD = 0.68) indicates a high level of self-reported AI influence on buying behaviour.

5.4 Pearson Correlation Analysis (Testing H_1)

Table 3. Pearson Correlation between AI Awareness and Purchase Decision Scores (n = 150). ** Correlation significant at $p < 0.01$ level (2-tailed).

Variable Pair	Pearson r	p-value	Decision
AI Awareness Score ↔ Purchase Decision Score	0.712**	< 0.001	H_1 Supported

The Pearson correlation coefficient of $r = 0.712$ ($p < 0.001$) indicates a strong, statistically significant positive association between AI awareness and purchase decision-making behaviour. The magnitude of this coefficient places the relationship in the 'large effect' range per Cohen's (1988) conventions ($r > 0.50$). H_1 is therefore supported. The direction of the relationship confirms that higher AI awareness is associated with greater self-reported AI influence on purchase behaviour- a finding that aligns with the HSM-based predictions of Zhao et al. (2025) and the S-O-R framework's proposition that stimuli processed through informed internal states produce stronger behavioural responses.

5.5 Simple Linear Regression Analysis (Testing H_2)

Table 4. Simple OLS Regression — AI Awareness as Predictor of Purchase Decision Behaviour (n = 150). Dependent variable: Purchase Decision Score. $F(1,148) = 146.89$, $p < 0.001$. SEE = Standard Error of the Estimate.

Model Summary	R	R^2	Adjusted R^2	SEE
AI Awareness → Purchase Decision	0.712	0.507	0.503	0.478

Coefficients	B	Std. Error	t	p-value
Constant (α)	1.241	0.218	5.693	< 0.001
AI Awareness Score (β_1)	0.703	0.058	12.12	< 0.001

The regression model is statistically significant at all conventional thresholds ($F(1,148) = 146.89$, $p < 0.001$). The R^2 value of 0.507 indicates that the AI Awareness Score alone explains 50.7% of the total variance in the Purchase Decision Score (substantial explanatory yield for a single-predictor model in consumer behaviour research). The standardised regression coefficient $\beta = 0.703$ ($p < 0.001$) indicates that for each one-unit increase in AI awareness, the purchase decision score increases by 0.703 units, net of error. H_2 is supported. The regression equation is:

Purchase Decision Score = 1.241 + 0.703 × (AI Awareness Score)

5.6 Independent Samples T-Test: Gender Differences (Testing H_3)

Table 5. Independent Samples T-Test — Gender Differences in AI Influence on Purchase Decision Behaviour (n = 150). Levene's test for equality of variances: $F = 0.84$, $p = 0.362$ (equal variances assumed).

Group	n	Mean	SD	Mean Diff.	t	p-value
Male	84	3.79	0.64	0.12	1.42	0.158
Female	66	3.67	0.71			

The t-test produces a non-significant result ($t(148) = 1.42$, $p = 0.158$, two-tailed). The mean difference between male ($M = 3.79$, $SD = 0.64$) and female ($M = 3.67$, $SD = 0.71$) respondents is 0.12, a difference that does not attain statistical significance. H_3 (the null of no gender difference) is retained. Levene's test confirmed the assumption of equal variances ($F = 0.84$, $p = 0.362$). This finding indicates that AI's influence on purchase decision-making is substantively uniform across gender in the Sangrur sample.

5.7 Summary of Hypothesis Testing

Table 6. Summary of Hypothesis Testing Results.

H	Hypothesis Statement	Test Used	Outcome
H_1	AI awareness is positively and significantly associated with AI-influenced purchase behaviour	Pearson r	Supported ✔
H_2	AI features significantly and positively influence final purchase decisions	OLS Regression	Supported ✔
H_3	No significant gender difference in AI influence on purchase decisions (null retained)	t-test	Retained ✔

6. DISCUSSION

6.1 AI Awareness as a Driver of Purchase Influence: Theoretical Interpretation

The strong positive correlation between AI awareness and purchase decision-making behaviour ($r = 0.712$) and the regression model's confirmation that awareness explains over half the variance in purchase outcomes ($R^2 = 0.507$) constitute the study's most significant empirical contribution. From a theoretical standpoint, these findings validate the S-O-R framework's core proposition in the Sangrur context: AI-generated stimuli (S) are mediated by consumer awareness states (O) to produce measurable purchase behaviours (R). Consumers who possess a more developed understanding of how AI features function are, in effect, better-calibrated organisms within the S-O-R architecture and this calibration appears to amplify rather than attenuate behavioural response.

This amplification effect awareness intensifying rather than moderating AI influence may appear counterintuitive. One might hypothesise that consumers who understand they are being algorithmically nudged would resist such nudges more actively. The data, however, support the opposite conclusion, consistent with the systematic processing pathway described by Zhao et al. (2025): consumers who understand that AI recommendations are based on their own behavioural history engage with those recommendations as relevance signals rather than intrusion vectors, thereby increasing their purchase propensity. The recommendation is not experienced as manipulation but as a form of curated assistance — a distinction that carries significant implications for how e-commerce platforms should communicate their AI features to consumers.

6.2 The Dynamic Pricing Knowledge Gap

The lowest mean score across both scales — 'Dynamic Pricing Awareness' ($M = 3.29$, $SD = 0.94$) deserves particular analytical attention. Dynamic pricing, the algorithmic adjustment of prices in real time based on supply, demand, and individual consumer profiling, is among the most commercially impactful AI mechanisms in e-commerce. Yet it is the mechanism that consumers in Sangrur understand least. The relatively high standard deviation (0.94 compared with 0.65–0.81 for other items) additionally indicates that awareness of dynamic pricing is distributed unevenly across the sample, suggesting heterogeneous exposure and comprehension.

This gap has direct ethical and regulatory implications. As Olan et al. (2024) noted, consumers whose data is most aggressively harvested for pricing purposes are frequently those least equipped to identify or contest the practice. A consumer in Sangrur who noticed that the price of a product changes between their first and second platform visit, but attributes this to random fluctuation rather than personalised algorithmic pricing, is a consumer who cannot make a fully informed purchase decision. This represents a consumer protection concern that neither platform operators nor Indian regulators have yet systematically addressed, and which this study's findings underscore.

6.3 Gender Neutrality of AI Influence

The absence of a statistically significant gender difference in AI's influence on purchase decisions ($t = 1.42$, $p = 0.158$) is a finding of positive valence from an equity perspective. It suggests that the AI-driven features deployed by major Indian e-commerce platforms are being perceived and responded to with broadly similar intensity by both male and female consumers in Sangrur. This may reflect the increasing diversity of product categories sold through AI-personalised recommendations — spanning electronics, fashion, groceries, and household goods such that the aggregate personalisation experience is similarly engaging across gender groups.

It bears noting, however, that the t-test operates on composite purchase decision scores and does not distinguish between product categories. The absence of an aggregate gender difference does not preclude the possibility of differential AI influence by category a question that future research with larger, category-stratified samples should investigate.

6.4 Contextual Significance: The Semi-Urban Punjab Consumer

The findings from Sangrur challenge a prevailing assumption in both academic and commercial discourse: that AI-driven commerce is primarily a metropolitan phenomenon. The consumers surveyed in this study are engaging with, and being meaningfully influenced by, the same AI systems that operate in Delhi and Mumbai and they are doing so with moderate-to-high awareness and strong behavioural responsiveness. The semi-urban Punjabi consumer is not a digital laggard awaiting inclusion in the digital economy; they are an active participant whose behaviours have simply gone unstudied.

This has strategic implications for e-commerce firms. The Sangrur data suggest that investment in AI personalisation features generates measurable returns in semi-urban markets. It also has policy implications: the same algorithmic systems that are reshaping consumption patterns in these towns are doing so in the absence of meaningful consumer education or regulatory oversight a combination that, if left unaddressed, risks embedding informational asymmetries that disadvantage precisely the consumers who are most dependent on digital platforms for access to goods and services.

7. CONCLUSION

7.1 Principal Conclusions

This study set out to examine whether, and to what degree, Artificial Intelligence influences the online purchase decision-making behaviour of consumers in Sangrur, Punjab. On the basis of primary survey data from 150 respondents and rigorous statistical analysis, the study reaches three principal conclusions.

First, AI awareness and AI-influenced purchase behaviour are strongly and significantly correlated in this population ($r = 0.712$, $p < 0.001$), validating the S-O-R framework's applicability to semi-urban Indian digital commerce contexts and supporting the view that informed consumers are more, not less, responsive to AI-generated cues.

Second, AI awareness is a robust predictor of purchase decision-making, accounting for 50.7% of the variance in purchase decision scores a finding that identifies consumer education as a lever for both commercial engagement and informed consumer agency. Third, AI's influence on purchase behaviour does not differ significantly by gender, indicating that the personalisation technologies deployed by major e-commerce platforms are reaching both male and female consumers in Sangrur with comparable effectiveness.

7.2 Implications for Theory

The study contributes to the theoretical literature by validating the S-O-R framework as an explanatory architecture for AI-influenced consumer behaviour in a semi-urban Indian context — a validation that extends the framework's geographic and demographic scope. It also provides empirical support for the systematic processing pathway proposed by Zhao et al. (2025) in the HSM literature, specifically by demonstrating that informed (systematic) engagement with AI recommendations is associated with higher purchase responsiveness.

7.3 Implications for Practice

For e-commerce platform operators, the study recommends investment in consumer-facing transparency mechanisms that explain, in accessible terms, how recommendation and pricing algorithms function. Such transparency is likely to increase both trust and engagement, as consumers transition from passive recipients of AI cues to active, aware participants in a personalised shopping experience. For Indian policymakers and consumer protection bodies, the dynamic pricing knowledge gap identified in this study warrants specific attention potentially through mandated disclosure requirements that ensure consumers are informed when pricing is algorithmically determined.

7.4 Limitations

The study's principal limitations are its geographic specificity (single town), cross-sectional design, and reliance on self-reported data. The single-predictor regression model, while powerful, does not account for known moderating variables such as platform trust, income elasticity, peer influence, or prior digital experience. These limitations define the agenda for future research.

7.5 Directions for Future Research

Future research should extend this study's framework to multi-site, multi-district, or multi-state designs to enable comparative analysis across different semi-urban Punjab contexts. Longitudinal designs would allow examination of how AI awareness and purchase responsiveness co-evolve over time. Qualitative methodologies — in-depth interviews, think-aloud protocols during actual shopping sessions would add interpretive depth to the quantitative findings. The inclusion of platform trust, digital literacy, and income as mediating or moderating variables in a structural equation model would substantially enrich the explanatory architecture employed here.

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