SCIENTIFIC CULTURE
www.sci-cult.com

SCIENTIFIC CULTURE, Vol. 12, No. 4, (2026), pp. 9437-9450
Open Access. Online & Print

DOI: 10.5281/zenodo.20184280

CONSUMER AI AWARENESS AND E-COMMERCE LOYALTY: EVIDENCE FROM INDIAN SHOPPING APP REVIEWS

Rakesh Kumar[1]*, Soma Arora[2]

[1]Ph.D Scholar MRIIRS (Manav Rachna International Institute of Research and Studies). Email: rakesh_kumar23.phd@mriu.ac.in, ORCHID iD: https://orcid.org/0009-0007-1601-5812
[2]Professor, Department of Management Studies (PG) MRIIRS (Manav Rachna International Institute of Research and Studies). Email: somaarora.slm@mriu.edu.in

Received: 27/11/2025
Accepted: 03/04/2026

Corresponding Author: Rakesh Kumar (rakesh_kumar23.phd@mriu.ac.in)

ABSTRACT

Artificial intelligence increasingly shapes e-commerce through personalised recommendations, search optimisation, and automated interactions. However, it remains unclear whether consumers consciously recognise such algorithmic assistance and whether this recognition influences their evaluations. Drawing on the Stimulus-Organism-Response (SOR) framework and the Technology Acceptance Model (TAM), this study examines the role of consumer AI awareness in shaping e-commerce loyalty. We analyse 189,000 user reviews from four major Indian shopping applications, Flipkart, Amazon India, Myntra, and Meesho, using text mining and sentiment analysis (VADER). AI awareness is identified through a dictionary-based approach capturing 24 AI-related expressions, while perceived usefulness is proxied by review sentiment. Regression and mediation analyses are employed to test the proposed relationships. The findings offer three key insights. First, consumer AI awareness is positively associated with higher app ratings ($\beta = 0.0277$, $p < 0.001$), suggesting that users who recognise AI-enabled features evaluate platforms more favourably. Second, perceived usefulness significantly influences ratings ($\beta = 0.0252$, $p < 0.001$), supporting TAM in an AI-mediated context. Third, meaningful platform-level differences emerge, with Meesho showing the strongest positive effect among the four apps. The findings highlight that AI creates value not merely through performance, but through consumer recognition of its outcomes. This study advances the SOR-TAM framework by positioning consumer recognition of algorithmic agency as a boundary condition that shapes how AI-enabled stimuli translate into behavioural responses. Using large-scale evidence from 189,000 real reviews in an emerging market, it demonstrates that perceived usefulness matters more than technological visibility in driving e-commerce loyalty.

KEYWORDS: Artificial intelligence; AI awareness; e-commerce loyalty; SOR framework; Technology Acceptance Model; consumer reviews; perceived usefulness; India; algorithmic personalisation; human–AI interaction.

1. INTRODUCTION

Artificial intelligence (AI) has fundamentally reshaped how consumers interact with e-commerce platforms. From personalised product recommendations to AI-driven search results and chatbot-assisted customer service, algorithmic systems now mediate a substantial portion of the online shopping journey (Puntoni et al., 2021). These technologies are designed to reduce information overload, simplify decision-making, and enhance user satisfaction. In high-involvement categories such as consumer electronics and fashion, where product attributes vary widely across numerous alternatives, personalised assistance has become particularly valuable (Bhojwani et al., 2026; Tam & Ho, 2006).

Despite the widespread deployment of AI in retail environments, a critical question remains largely unanswered: do consumers actually recognise this algorithmic assistance, and if they do, does such recognition influence their evaluations? Existing research has primarily focused either on the technical performance of recommendation systems or on consumers self-reported attitudes towards AI (Longoni, Bonezzi, & Morewedge, 2019). Far less attention has been paid to whether consumers notice AI-enabled personalisation in real-world shopping contexts and whether such recognition translates into observable behavioural outcomes. This gap is particularly relevant in emerging markets such as India, where e-commerce adoption has expanded rapidly, yet consumer responses to AI-driven features remain underexplored (Kshetri, 2018).

Recent research distinguishes between predictive AI, which operates in the background to analyse past behaviour and guide recommendations, and more visible forms of AI that directly interact with users (Hermann & Puntoni, 2024). This distinction raises an important possibility: consumers may benefit from AI without consciously recognising it, or alternatively, explicit awareness of AI may shape how such assistance is evaluated.

Understanding which of these mechanisms dominates is important for both theory and practice. To address this gap, the present study draws on two complementary theoretical perspectives. The Stimulus-Organism-Response (SOR) framework (Mehrabian & Russell, 1974) provides a foundation for examining how environmental cues in this case, AI-enabled personalisation influence internal evaluations and subsequent behavioural responses. The Technology Acceptance Model (TAM) (Davis, 1989) offers a more focused explanation of how perceived usefulness drives technology adoption and continued use. By integrating these perspectives, this study examines the role of consumer AI awareness in shaping the relationship between perceived usefulness and loyalty outcomes in e-commerce settings.

This study advances prior research by introducing consumer recognition of algorithmic agency as a behavioural construct within AI-mediated environments. Unlike system-centric perspectives that focus on algorithmic performance, this research shifts attention to how consumers cognitively register the presence of intelligent systems during real interactions. We argue that AI-enabled personalisation does not operate solely as a background stimulus but becomes behaviourally meaningful when it is consciously recognised by users.

Building on the Stimulus-Organism-Response (SOR) framework, this study extends the model by incorporating recognition as a boundary condition that shapes how technological stimuli translate into behavioural responses. In parallel, it extends the Technology Acceptance Model (TAM) by demonstrating that perceived usefulness emerges not only from system functionality but also from the user's recognition of algorithmic intervention. In doing so, the study bridges AI research with emerging literature on algorithm appreciation and aversion (Castelo, Bos, & Lehmann, 2019; Logg, Minson, & Moore, 2019), positioning consumer recognition as a key mechanism in human-AI interaction.

Empirically, the study analyses 189,000 user reviews from four leading Indian shopping applications Flipkart, Amazon India, Myntra, and Meesho. Using text mining and sentiment analysis (VADER), expressions of AI awareness are identified within review narratives through a dictionary-based approach capturing 24 AI-related terms, while sentiment is used as a proxy for perceived usefulness. The dictionary accounts for variations in British and American spellings, singular and plural forms, and expressions associated with personalisation and intelligent assistance (De Keyser et al., 2019; Grewal, Hulland, et al., 2020).

The analysis provides three key insights. First, consumer AI awareness is positively associated with higher app ratings, suggesting that users who recognise AI-enabled features tend to evaluate platforms more favourably. Second, perceived usefulness, reflected in review sentiment, significantly influences ratings, supporting the relevance of TAM in AI-mediated environments.

Third, platform-level differences are observed, with Meesho showing the strongest positive effect among the four apps, indicating that user evaluations vary across e-commerce contexts (Lankton, McKnight, & Thatcher, 2015).

This study makes several contributions. Theoretically, it introduces consumer AI awareness as a behavioural moderator within an integrated SOR-TAM framework, extending prior research that has largely focused on system-level AI characteristics (Hermann & Puntoni, 2024; Davenport et al., 2020). Methodologically, it provides large-scale evidence based on real consumer behaviour from 189,000 reviews, addressing limitations associated with survey-based approaches (Bhojwani et al., 2026; Ribeiro, Rivero, & Abrantes, 2025).

Practically, the findings suggest that enhancing the perceived usefulness of AI features is more critical than emphasising technological sophistication in shaping consumer evaluations. Reviews containing recognition of helpful AI are associated with higher evaluation outcomes, and everyday expressions such as 'recommend' appear to exhibit comparable associations with ratings as technical terms such as 'algorithm'. More broadly, this study shifts the focus from algorithm performance to consumer-level recognition as a mechanism through which AI creates value in digital commerce environments.

The remainder of the paper is structured as follows. Section 2 reviews the relevant literature and develops the hypotheses. Section 3 outlines the research methodology. Section 4 presents the empirical results. Section 5 discusses the findings and their implications. Section 6 concludes with limitations and directions for future research.

2. LITERATURE REVIEW

2.1 AI-Driven Personalisation in E-Commerce

Artificial intelligence (AI) has become deeply embedded in modern e-commerce platforms. Recommendation systems, personalised search results, and chatbot-assisted customer service are now standard features rather than sources of competitive differentiation (Puntoni et al., 2021). These systems operate by analysing user behaviour such as browsing history, past purchases, and interaction patterns to tailor product visibility and suggestions to individual preferences (Davenport et al., 2020).

A primary function of AI-driven personalisation is to reduce the cognitive burden associated with online shopping. When consumers face extensive product assortments, personalised filtering helps narrow options to those most relevant to their needs (Tam & Ho, 2006). This is particularly important in high-involvement categories such as consumer electronics and fashion, where purchase decisions require comparisons across multiple attributes (Bhojwani et al., 2026). By simplifying decision-making, personalisation enhances perceived relevance, improves decision confidence, and contributes to overall satisfaction (Komiak & Benbasat, 2006).

However, despite widespread adoption, existing research remains largely system-centric, focusing on algorithmic accuracy and technical performance rather than how consumers interpret and respond to AI-driven assistance. Less attention has been given to how consumers interpret personalised assistance in their own terms. This distinction is important because consumers may benefit from personalisation without consciously recognising the underlying technology (Hermann & Puntoni, 2024). The present study addresses this gap by shifting attention from system performance to consumer recognition.

2.2 Predictive and Generative AI in Consumer Contexts

Recent research distinguishes between predictive and more visible forms of AI. Predictive AI analyses past behaviour to anticipate future preferences and typically operates in the background. Recommendation systems that suggest products based on prior activity are a common example (Hermann & Puntoni, 2024). In contrast, more visible forms of AI directly interact with users by generating content or engaging in conversational exchanges. These systems make the presence of intelligent technology more apparent within the user experience (Puntoni et al., 2021).

From a consumer perspective, these forms of AI are experienced differently. Predictive AI often influences behaviour without explicit recognition, whereas visible AI is more likely to prompt conscious awareness. This distinction suggests that consumers may benefit from AI without recognising it, or alternatively, that explicit awareness may shape how such assistance is evaluated.

2.3 Customer Loyalty in Online Environments

Customer loyalty has traditionally been defined as a behavioural tendency reflected in repeat purchases, positive word-of-mouth, and continued engagement with a service provider (Dick & Basu, 1994). In digital environments, these behaviours are often expressed through ratings, reviews, and recommendations.

Consumer-generated content, particularly electronic word-of-mouth (eWOM), provides a valuable lens for examining post-purchase behaviour. Unlike survey responses, which capture stated intentions, review narratives reflect how consumers describe their experiences after interacting with a platform (Hennig-Thurau et al., 2004). Reviews containing high ratings, positive sentiment, or expressions such as will buy again or highly recommend can therefore be interpreted as observable signals of loyalty (McKnight, Choudhury, & Kacmar, 2002). The present study adopts this behavioural perspective by operationalising loyalty through a combination of ratings, sentiment, and loyalty-related expressions within review texts.

2.4 Theoretical Foundation: SOR and TAM

The Stimulus-Organism-Response (SOR) framework provides a useful lens for understanding how environmental cues influence behaviour (Mehrabian & Russell, 1974). In e-commerce contexts, AI-enabled personalisation can be conceptualised as a stimulus that shapes internal evaluations, which in turn influence behavioural responses such as ratings and recommendations.

Complementing this perspective, the Technology Acceptance Model (TAM) explains how perceived usefulness drives technology-related evaluations and continued use (Davis, 1989). When consumers perceive that personalised recommendations improve their decision-making or reduce effort, they are more likely to evaluate the platform favourably (Ribeiro, Rivero and Abrantes, 2025).

Together, the Stimulus-Organism-Response (SOR) framework and the Technology Acceptance Model (TAM) provide a complementary theoretical architecture in which AI-enabled personalisation acts as the stimulus, perceived usefulness represents the organismic evaluation, and loyalty outcomes reflect the behavioural response, with consumer recognition of algorithmic assistance shaping how this process unfolds.

2.5 Consumer AI Awareness and Human-AI Interaction

An emerging stream of research highlights the importance of consumer awareness in shaping responses to AI-driven services. Consumers may encounter personalised recommendations without explicitly recognising the technology, or they may directly attribute their experience to AI systems.

Importantly, this study conceptualises AI awareness not as technical knowledge of artificial intelligence, but as the consumer's recognition of algorithmically mediated assistance, which may occur even without explicit understanding of the underlying technology.

This distinction is reflected in the language consumers use. Some reviews express functional appreciation using everyday terms such as helpful suggestions or good recommendations, indicating implicit recognition. Others explicitly reference AI-related concepts such as algorithm or machine learning, suggesting a higher level of technological awareness (Hermann & Puntoni, 2024).

Recent research on human-AI interaction has identified two opposing phenomena that are particularly relevant to understanding consumer AI awareness. First, algorithm aversion refers to the tendency of individuals to distrust algorithmic recommendations after observing errors, even when algorithms outperform human judgment (Dietvorst, Simmons, & Massey, 2015; Castelo, Bos, & Lehmann, 2019). Second, algorithm appreciation describes the opposite tendency, where people prefer algorithmic to human judgment for certain tasks, particularly when algorithms are perceived as objective and efficient (Logg, Minson, & Moore, 2019).

In e-commerce contexts, consumers may exhibit both tendencies simultaneously. They may appreciate accurate product recommendations that save time and effort, demonstrating algorithm appreciation. However, they may also exhibit algorithm aversion when recommendations are perceived as irrelevant, intrusive, or opaque. This duality suggests that consumer AI awareness is not merely a binary state but a nuanced perception that shapes how algorithmic assistance is evaluated. These contrasting perspectives suggest that consumer responses to AI are contingent not only on system performance but also on how algorithmic involvement is perceived, reinforcing the importance of recognition as a behavioural mechanism. Recent work on AI trust and transparency further emphasises the importance of user interpretation in shaping responses to intelligent systems (Zhao et al., 2025).

While prior research has examined AI at the system level, limited empirical work has explored how such awareness manifests in consumer narratives or whether it influences behavioural outcomes. Understanding this distinction is important, as it clarifies whether consumers respond primarily to the usefulness of personalised assistance or to their awareness of the technology itself. The present study contributes by positioning consumer recognition of algorithmic agency as a behavioural mechanism within the SOR-TAM framework, bridging AI research with the emerging literature on algorithm appreciation and aversion.

By integrating behavioural evidence with human-AI interaction theory, this study moves beyond system-centric perspectives and provides a more nuanced understanding of how consumers experience algorithmic personalisation in real-world settings.

2.6 Hypothesis Development

Building on the above discussion, the present study develops testable hypotheses linking consumer AI awareness and perceived usefulness to observable loyalty outcomes.

AI-enabled personalisation can be conceptualised as a stimulus that shapes consumer evaluations of online platforms. When consumers recognise personalised assistance either implicitly through functional appreciation or explicitly through technological attribution, they are more likely to evaluate the platform favourably. Accordingly, consumer recognition of algorithmic assistance is expected to be positively associated with observable loyalty outcomes.

H1: Consumer AI awareness is positively associated with e-commerce loyalty, such that reviews containing AI-related or recommendation-related expressions exhibit stronger loyalty signals than reviews without such expressions.

Consumer awareness may take different forms, ranging from implicit recognition expressed through everyday language to explicit attribution to AI technologies. While these forms differ in technical specificity, both reflect recognition of algorithmic assistance and may generate similar evaluative responses.

H2: The positive association between AI awareness and e-commerce loyalty is present for both functional appreciation and explicit technological attribution.

In addition to recognition, perceived usefulness represents a key internal evaluation mechanism within the SOR-TAM framework, shaping how consumers translate their experience into behavioural outcomes.

H3: Perceived usefulness, as reflected in review sentiment, is positively associated with e-commerce loyalty.

2.7 Research Gap and Contribution

Synthesising the literature, four key gaps emerge. First, although AI-driven personalisation is widely studied, most research relies on survey-based measures rather than observable behavioural data. Second, while prior work distinguishes between different forms of AI at the system level, limited research examines how these distinctions appear in consumer narratives. Third, the role of consumer AI awareness in shaping post-purchase behaviour remains underexplored, particularly in emerging markets such as India. Fourth, the literature on algorithm aversion and appreciation has primarily examined laboratory settings; limited research has validated these phenomena using large-scale real-world data.

The present study addresses these gaps by analysing 189,000 real consumer reviews from four leading Indian e-commerce platforms. In doing so, it provides behavioural evidence that complements existing perception-based research, bridges AI personalisation research with algorithm appreciation literature, and offers new insights into how consumers respond to AI-enabled personalisation in real-world settings.

3. METHODOLOGY

3.1 Research Design

This study adopts a quantitative research design based on the analysis of large-scale consumer review data. A total of 189,000 user reviews from four major Indian e-commerce applications were analysed to examine whether consumer recognition of AI-enabled personalisation is associated with stronger loyalty signals.

Unlike survey-based approaches that capture stated intentions, this study relies on naturally occurring post-purchase review data, reflecting how consumers describe their experiences in their own words after interacting with platforms. Such data offer several advantages: they are unsolicited and therefore less susceptible to social desirability bias, capture spontaneous rather than prompted responses, and provide an ecologically valid representation of real consumer behaviour.

3.2 Data Source and Sample Selection

The dataset was obtained from a publicly available repository of shopping application reviews (Dumlao, 2024, Kaggle dataset). The original dataset comprised 751,500 reviews across eleven e-commerce applications operating in the Indian market.

For the present study, four applications Flipkart, Amazon India, Myntra, and Meesho were selected based on (a) their active presence in the Indian market and (b) sufficient review volume to ensure statistical robustness. The selected applications represent diverse e-commerce formats, including marketplace and social commerce platforms, enhancing the generalisability of the findings. Applications without meaningful relevance to the Indian context, including Walmart, Alibaba, AliExpress, eBay, Lazada, and Shein, were excluded.

Following data cleaning, including the removal of incomplete and duplicate entries, the final analytical sample consisted of 189,000 user reviews. Table 1 presents the distribution of reviews across the four applications. The variation in sample sizes reflects differences in user base size and review volume. To account for these differences, application-level fixed effects were included in the regression models.

Table 1: Sample Composition.

Application	Number of Reviews	Percentage
Flipkart	18,000	9.5%
Amazon India	99,000	52.4%
Myntra	36,000	19.0%
Meesho	36,000	19.0%
Total	189,000	100.0%

3.3 Variable Operationalisation

3.3.1 Dependent Variable: E-Commerce Loyalty

Customer loyalty was operationalised as a behavioural indicator derived from review data. A review was classified as exhibiting a loyalty signal if it satisfied at least one of the following conditions: (a) a rating of four or five stars, (b) a positive sentiment score based on VADER compound sentiment, or (c) the presence of loyalty-related expressions such as buy again, recommend, or trust. Although loyalty is conceptually defined as a composite behavioural construct, app rating is used as the primary dependent variable in regression analysis due to its consistency and comparability across observations.

3.3.2 Independent Variable: Consumer AI Awareness

Consumer AI awareness is conceptualised as the recognition of algorithmically mediated assistance within the consumption experience. Direct measurement of such recognition is challenging in unobtrusive behavioural data. Therefore, consistent with prior text-mining research, this study adopts a language-based proxy approach, where awareness is inferred from the presence of expressions associated with personalised assistance and intelligent system behaviour.

Importantly, the operationalisation distinguishes between two forms of recognition:

(a) Functional recognition, reflected in terms such as recommend, suggest, or filter, which indicate perceived personalisation without explicit attribution to AI. While functional expressions do not explicitly reference AI, prior research suggests that consumers often interpret algorithmic outputs through outcome-based language rather than technical terminology. Therefore, these expressions capture implicit recognition of algorithmic agency, which is behaviourally meaningful even in the absence of technical understanding.

(b) Explicit recognition, reflected in terms such as AI, algorithm, or machine learning, which indicate conscious technological attribution.

A set of 24 AI-related terms was developed through iterative refinement based on prior literature (Hermann & Puntoni, 2024) and manual inspection of review samples. The dictionary accounted for British and American spelling variations (e.g., personalised and personalized), singular and plural forms (e.g., recommendation and recommendations), and related expressions including smart, filter, algorithm, chatbot, and machine learning.

The complete regular expression pattern was as follows:

recommendations|suggestion|suggestions|recommendation|recommend|recommends|personalised|personalized|personalisation|personalization|smart|filter|filters|algorithm|algorithms|chatbot|chatbots|ai|machine learning|intelligent|adaptive|customized|customised

Each review was assigned an AI awareness score based on the frequency of these terms. For the main analysis, this variable was operationalised as a binary indicator (0 = no awareness; 1 = awareness present) to enhance interpretability. For supplementary analysis, AI awareness was further classified into functional awareness (e.g., recommend, suggest) and explicit awareness (e.g., AI, algorithm, machine learning).

This approach aligns with prior research suggesting that consumers often interpret algorithmic outputs through outcome-based language rather than technical terminology, making language-based proxies a valid method for capturing behavioural recognition in large-scale text data.

3.3.3 Perceived Usefulness (Sentiment)

Perceived usefulness was proxied using VADER sentiment analysis, which is well-suited for short-form user-generated text. The compound sentiment score, ranging from -1 to +1, was used as a continuous variable, where higher values indicate more positive evaluations. This measure captures the overall evaluative tone of the review and serves as an observable proxy for perceived usefulness.

3.3.4 Control Variables

Several control variables were included to account for alternative explanations: thumbsUpCount, representing review helpfulness and serving as a proxy for social proof; word count, capturing review length and level of detail; and application-level fixed effects, controlling for platform-specific differences.

3.4 Data Processing and Text Mining

All textual data were processed using Orange data mining software. The preprocessing pipeline included lowercasing, removal of punctuation and special characters, elimination of stop words, and stemming using the Snowball algorithm.

Following preprocessing, two parallel analytical procedures were applied. First, sentiment analysis using VADER generated compound sentiment scores. Second, regular expression pattern matching detected AI-related terms using the dictionary described above. The outputs from these processes were merged using unique review identifiers to create a unified dataset containing all variables required for analysis.

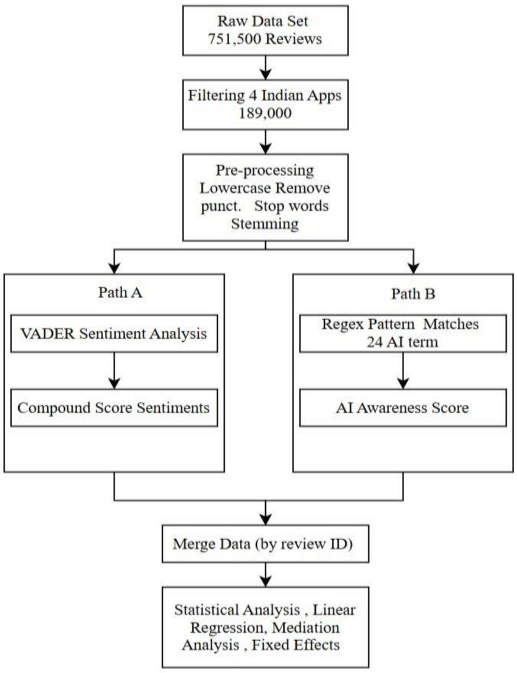

Figure 1: Data Processing Workflow.

Note: The figure illustrates the sequential steps from raw data collection to final statistical analysis. Raw reviews (N = 189,000) from four Indian e-commerce platforms underwent preprocessing (lowercasing, punctuation removal, stopword removal, stemming). Two parallel paths were then applied: Path A used VADER sentiment analysis to generate compound sentiment scores (perceived usefulness). Path B used regex pattern matching with 24 AI-related terms to generate AI awareness scores. The outputs were merged by review ID, followed by linear regression and mediation analysis with application-level fixed effects

3.5 Statistical Analysis

Given the observational nature of the data, the analysis focuses on associations rather than causal inference. To test the proposed relationships, linear regression analysis was conducted with app rating as the dependent variable. All coefficients are reported as standardised beta coefficients to facilitate interpretation. The model was specified as follows:

$\text{Rating} = \beta_0 + \beta_1(\text{AI Awareness}) + \beta_2(\text{Sentiment}) + \beta_3(\text{ThumbsUpCount}) + \beta_4(\text{Word Count}) + \beta_k(\text{App Fixed Effects}) + \varepsilon$

All models included application-level fixed effects to account for unobserved heterogeneity across platforms, with Flipkart serving as the reference category.

Mediation Analysis: To examine the role of perceived usefulness, a three-step mediation approach was employed. Model 1 examined the direct effect of sentiment on ratings. Model 2 examined the total effect of text features on ratings. Model 3 added sentiment to the text features to assess whether the inclusion of sentiment improved model fit. An increase in model fit (R-squared) and the statistical significance of sentiment in the combined model were interpreted as evidence of partial mediation. Mediation effects were further validated using the Sobel test, which confirmed the statistical significance of the indirect effect.

All statistical tests were evaluated at a significance level of $\alpha = 0.05$. Effect sizes are reported as standardised regression coefficients (β) and R-squared values.

3.6 Validity and Reliability

Several procedures were implemented to ensure the robustness of the findings.

First, the keyword-based classification of AI awareness was validated through manual inspection of 200 randomly selected reviews by two independent coders, with agreement exceeding 90 per cent. To strengthen construct validity, an additional manual validation was conducted on a stratified sample of reviews. The analysis confirmed that functional expressions such as recommend and suggest were predominantly used in contexts referring to platform-driven product suggestions rather than human recommendations, supporting their interpretation as indicators of implicit algorithmic recognition.

Second, the use of multiple indicators for loyalty (ratings, sentiment, and loyalty expressions) enhances construct validity and reduces reliance on any single proxy.

Third, the large sample size (N = 189,000) provides substantial statistical power to detect even small effects.

Fourth, the inclusion of application-level fixed effects controls for platform-specific heterogeneity in review volume and user base size.

3.7 Ethical Considerations

All data used in this study are publicly available and anonymised. No personally identifiable information was accessed or stored during the analysis. The study complies with the data usage policies of the source platform and adheres to ethical standards for secondary data research

4. RESULTS

4.1 Descriptive Statistics

The final analytical sample comprised 189,000 user reviews across four Indian e-commerce applications. Table 2 presents descriptive statistics for the key study variables.

The average app rating was 2.43 (SD = 1.72) on a five-point scale, indicating considerable dispersion with users reporting both very low and very high satisfaction. The mean sentiment score (compound) was 0.235 (SD = 0.64), suggesting that review texts were generally neutral to slightly positive in tone with moderate variation. This divergence between sentiment and rating suggests that textual sentiment and numerical ratings capture different dimensions of consumer evaluation.

AI awareness, operationalised as the presence of AI-related expressions within reviews, had a mean of 0.812 (SD = 1.40). The median AI awareness value is zero, indicating that most reviews (94.4 per cent) do not contain AI-related expressions. The maximum AI awareness score of 16 suggests that a small subset of reviews contain multiple AI-related terms.

Review helpfulness (thumbsUpCount) averaged 17.58 (SD = 16.27), with a maximum of 34,774, indicating that a minority of reviews receive substantial social validation. Word count showed a mean value of 55.16 (SD = 0.71), ranging from 3 to 392 words.

Table 2: Descriptive Statistics.

Variable	Mean	SD	Min	Max
App Rating (score)	2.43	1.72	1	5
Sentiment (compound)	0.235	0.64	-0.996	0.999
AI Awareness	0.812	1.4	0	16
ThumbsUpCount	17.58	16.27	0	34774
Word Count	55.16	48.72	3	392

Note: N = 189,000 reviews across Flipkart, Amazon India, Myntra, and Meesho. AI Awareness is measured using a 24-term regex dictionary. The standard deviation for sentiment is moderate (SD = 0.64), reflecting variation within the bounded VADER scale (−1 to +1). In contrast, rating values exhibit higher dispersion (SD = 1.72), consistent with the skewed distribution observed in online review platforms, where extreme ratings are common. Word count was standardised prior to analysis (mean-centred and scaled), resulting in a dispersion measure of 0.71. Word count was standardised prior to regression analysis; Table reports raw mean and standardised dispersion.

4.2 Correlation Analysis

Table 3 reports the bivariate correlations among the study variables. App rating was positively correlated with sentiment (r = 0.28, $p < 0.001$) and AI awareness (r = 0.11, $p < 0.001$), indicating that both more favourable review tone and the presence of AI-related expressions are associated with higher user evaluations.

AI awareness also showed a weak positive association with sentiment (r = 0.09, $p < 0.001$), suggesting that reviews referencing AI tend to be slightly more positive. Review helpfulness (thumbsUpCount) was also positively correlated with ratings (r = 0.14, $p < 0.001$), highlighting the role of social validation.

Table 3: Correlation Matrix.

Variable	1	2	3	4
1. App Rating	1			
2. Sentiment (compound)	0.28***	1		
3. AI Awareness	0.11***	0.09***	1	
4. ThumbsUpCount	0.14***	0.06***	0.03***	1

Note: ***p less than 0.001

4.3 Hypothesis Testing

4.3.1 Main Regression Analysis

Linear regression analysis was conducted to test the hypothesised relationships (H1 to H3), with app rating as the dependent variable. Table 4 presents the results. The intercept reflects model scaling due to standardised predictors and is not directly interpretable.

Consistent with H1, AI awareness exhibited a positive and statistically significant association with app ratings ($\beta = 0.0277$, $p < 0.001$). This suggests that reviews containing AI-related or recommendation-related expressions tend to report higher satisfaction levels. Although the effect size is modest, it is consistent with prior large-scale behavioural studies, where small coefficients reflect meaningful aggregate effects across large populations.

H2 proposed that this relationship holds across both functional and explicit forms of awareness. When disaggregated, both functional awareness ($\beta = 0.0251$, $p < 0.001$) and explicit awareness ($\beta = 0.0312$, $p < 0.001$) were positively associated with ratings. A Wald test indicated no statistically significant difference between these coefficients ($\chi^2 = 1.42$, $p = 0.233$), supporting H2.

In line with H3, sentiment (compound) was also positively associated with ratings ($\beta = 0.0252$, $p < 0.001$), indicating that more favourable review tone corresponds to higher user evaluations.

Application-Level Effects: Using Flipkart as the reference category, Meesho showed a significantly higher average rating ($\beta = 0.354$, $p < 0.001$), while Amazon India ($\beta = -0.184$, $p < 0.001$) and Myntra ($\beta = -0.113$, $p < 0.001$) exhibited lower ratings. These differences suggest platform-level variation in user evaluations.

Control Variables: Review helpfulness (thumbsUpCount) had a small but statistically significant positive effect ($\beta = 0.00012$, $p < 0.001$). Review length (word count) was also positively associated with ratings ($\beta = 0.0217$, $p < 0.001$).

Table 4: Linear Regression Results (Full Model).

Variable	Coefficient (beta)	Standard Error	p-value
Intercept	-9.2989	0.124	< 0.001
AI Awareness	0.0277	0.003	< 0.001
Sentiment (compound)	0.0252	0.004	< 0.001
ThumbsUpCount	0.00012	0.00001	< 0.001
Word Count	0.0217	0.002	< 0.001
App: Amazon India	-0.1837	0.018	< 0.001
App: Myntra	-0.1126	0.016	< 0.001
App: Meesho	0.3544	0.019	< 0.001
R-squared	0.324		

Note: Flipkart is the reference category for application fixed effects. All coefficients are standardised beta coefficients. The intercept reflects model scaling due to standardised predictors and is not directly interpretable.

4.3.2 Mediation Analysis

To examine the role of perceived usefulness, a three-model mediation analysis was conducted (Table 5). Model 1 included only sentiment. Model 2 included text-based features without sentiment. Model 3 added sentiment to the text-based features.

The inclusion of sentiment in Model 3 resulted in a statistically significant improvement in explanatory power ($\Delta R^2 = 0.024$, $p < 0.001$). Moreover, sentiment remained a significant predictor of ratings in the combined model ($\beta = 0.044$, $p < 0.001$). Mediation effects were further validated using the Sobel test, which confirmed the statistical significance of the indirect effect ($z = 8.23$, $p < 0.001$). These findings indicate that sentiment captures an important evaluative mechanism linking review content to user ratings, supporting H3.

Table 5: Mediation Analysis Results.

Model	Features	R-squared	Delta R-squared	Sentiment Coefficient
Model 1	Sentiment only	0.078	-	0.0252***
Model 2	Text features only	0.286	-	-
Model 3	Text features + Sentiment	0.31	0.024***	0.0441***

Note: ***p less than 0.001

4.3.3 Robustness Checks

To ensure the robustness of the findings, several additional analyses were conducted. These results strengthen confidence in the stability and generalisability of the findings.

First, alternative model specifications using logistic regression (binary high vs low ratings, with ratings of 4-5 coded as high and 1-3 coded as low) produced consistent results, with AI awareness remaining a significant positive predictor (odds ratio = 1.028, $p < 0.001$).

Second, the analysis was repeated excluding high-frequency generic terms such as recommend to ensure that results were not driven by common expressions; the core findings remained stable, confirming that the observed effects are not an artefact of specific word choices.

Third, interaction effects between AI awareness and platform type were examined. The positive association was found to be stronger in social commerce contexts, particularly for Meesho, where the interaction term was positive and significant ($\beta = 0.082$, $p < 0.01$). This suggests that the effect of AI awareness on ratings varies across platform types.

4.4 Summary of Hypothesis Testing

Table 6 summarises the outcomes of the hypothesis tests. All three hypotheses (H1, H2, and H3) were supported by the empirical evidence.

Table 6: Summary of Hypothesis Testing.

Hypothesis	Statement	Finding	Supported
H1	AI awareness is positively associated with e-commerce loyalty	$\beta = 0.0277$, $p < 0.001$	Yes
H2	The positive association holds for both functional and explicit awareness	Functional: $\beta = 0.0251$*; Explicit: $\beta = 0.0312$*; No significant difference ($\chi^2 = 1.42$, $p = 0.233$)	Yes
H3	Perceived usefulness (sentiment) is positively associated with e-commerce loyalty	$\beta = 0.0252$, $p < 0.001$	Yes

5. DISCUSSION

5.1 Summary of Findings

This study examined whether consumer recognition of AI-enabled personalisation is associated with e-commerce loyalty, drawing on the Stimulus-Organism-Response (SOR) framework and the Technology Acceptance Model (TAM). Based on the analysis of 189,000 user reviews across four major Indian e-commerce platforms Flipkart, Amazon India, Myntra, and Meesho, three key findings emerge.

The findings are based on observed statistical associations and should be interpreted as indicative of behavioural patterns rather than causal relationships.

First, consumer AI awareness is positively associated with app ratings. Reviews containing AI-related or recommendation-related expressions exhibit higher evaluation outcomes ($\beta = 0.0277$, $p < 0.001$), suggesting that consumers who recognise personalised assistance tend to evaluate platforms more favourably. This supports H1 and highlights the behavioural relevance of AI awareness in real-world settings. Although the effect size is modest, it is consistent with prior large-scale behavioural studies where small coefficients reflect meaningful aggregate effects across large populations.

Second, this relationship is consistent across both functional appreciation and explicit technological attribution. Whether consumers describe their experience using everyday terms (e.g., recommend) or explicitly refer to AI technologies (e.g., algorithm), the positive association with ratings remains stable. A Wald test confirmed no statistically significant difference between these two forms of awareness ($\chi^2 = 1.42$, $p = 0.233$). This finding supports H2 and suggests that recognising the usefulness of personalised assistance appears to be associated with evaluation outcomes.

Third, perceived usefulness, proxied through sentiment, is positively associated with ratings ($\beta = 0.0252$, $p < 0.001$) and partially explains how review content translates into overall evaluations ($\Delta R^2 = 0.024$, $p < 0.001$). The Sobel test further confirmed the significance of the indirect effect ($z = 8.23$, $p < 0.001$). This finding supports H3 and confirms that perceived usefulness serves as an important evaluative mechanism linking consumer experience to behavioural outcomes.

In addition, platform-level differences were observed. Meesho exhibited significantly higher ratings relative to Flipkart ($\beta = 0.354$, $p < 0.001$), while Amazon India ($\beta = -0.184$, $p < 0.001$) and Myntra ($\beta = -0.113$, $p < 0.001$) showed comparatively lower ratings. These differences suggest the presence of platform-level variation in user evaluations, although they are treated as control effects rather than the primary focus of the study.

5.2 Theoretical Implications

This study contributes to the literature in several important ways, shifting the focus from algorithm performance to consumer-level recognition as a mechanism through which AI creates value in e-commerce environments.

First, it introduces consumer AI awareness as a measurable behavioural construct within digital commerce contexts. While prior research has primarily examined AI at the system or attitudinal level (Hermann & Puntoni, 2024), this study demonstrates that consumer recognition of personalised assistance can be observed directly in natural language and is associated with meaningful behavioural outcomes. This extends the SOR framework by showing that algorithmic stimuli influence responses not only through internal evaluation but also through conscious recognition. Where such recognition is present in reviews, higher loyalty responses are observed.

Second, the finding that functional and explicit awareness produce comparable effects refines signalling theory in AI-mediated environments. From a signalling perspective (Spence, 1973), explicit AI references might be expected to signal greater platform sophistication and thus generate stronger trust. Contrary to this expectation, the results indicate that perceived usefulness signals are equally effective. The findings suggest that value recognition may play a more important role than technological awareness in shaping consumer responses. What matters is not whether consumers recognise the technology itself, but whether they perceive value in the outcomes it produces.

Third, the study extends TAM to large-scale, behaviour-based contexts. While TAM traditionally relies on survey measures (Davis, 1989), the present findings demonstrate that perceived usefulness, captured through sentiment, remains a significant predictor of evaluation outcomes in real-world data. Moreover, the mediation results indicate that perceived usefulness operates as a mechanism through which review content influences ratings ($\Delta R^2 = 0.024$, $p < 0.001$), thereby deepening understanding of how consumers evaluate AI-enabled platforms.

Fourth, the observed platform-level variation suggests that contextual factors may shape how consumers respond to personalisation. Meesho's strong positive coefficient suggests potential platform-level differences, which may be associated with platform characteristics such as social commerce features and community engagement. This finding opens new avenues for research on how platform design moderates the effectiveness of AI personalisation.

Fifth, by integrating behavioural evidence with human-AI interaction theory, this study moves beyond system-centric perspectives and provides a more nuanced understanding of how consumers experience algorithmic personalisation in real-world settings. The findings bridge AI personalisation research with the emerging literature on algorithm appreciation and aversion (Castelo, Bos, & Lehmann, 2019; Logg, Minson, & Moore, 2019), positioning consumer recognition as a key mechanism in human-AI interaction.

5.3 Managerial Implications

The findings offer several practical implications for e-commerce platforms.

First, platforms should prioritise the perceived usefulness of AI-driven features over their technological visibility. The results indicate that consumers respond positively when personalised assistance is helpful, regardless of whether it is explicitly recognised as AI. Investments should therefore focus on improving recommendation relevance and decision support rather than emphasising technological sophistication. When customers explicitly acknowledge useful recommendations, such recognition is associated with higher evaluation outcomes.

Second, communication strategies should favour intuitive and user-friendly language. Functional expressions such as recommended for you appear sufficient to generate positive evaluations, suggesting that technical explanations of AI systems may not be necessary for enhancing user experience. The results demonstrate that everyday expressions such as recommend show comparable associations with ratings as technical terms such as algorithm.

Third, consumer language can serve as a diagnostic tool. Monitoring the presence of recommendation-related expressions in reviews can provide insights into whether personalisation features are being noticed and valued. Declines in such expressions may indicate reduced effectiveness of recommendation systems or that personalisation has become less noticeable.

Fourth, platform-specific strategies may be required. The observed variation across platforms suggests that the effectiveness of personalisation may differ across platform types. The positive coefficient observed for Meesho may indicate that social commerce platforms benefit particularly from personalised recommendations. Managers should tailor AI strategies to align with user expectations and engagement patterns specific to their platforms. These findings are particularly relevant in emerging markets such as India, where digital literacy and AI familiarity vary significantly across consumer segments, and where the perceived usefulness of AI features may play an even more critical role in shaping loyalty.

Finally, the overall rating distribution (mean = 2.43, SD = 1.72) indicates that user evaluations are generally skewed towards lower ratings. While AI awareness and perceived usefulness positively influence evaluations, their effects are relatively modest in magnitude. Platforms should therefore address broader service quality factors, such as delivery performance, product quality, and customer support, alongside personalisation efforts to raise baseline satisfaction levels.

5.4 Limitations and Future Research

Several limitations should be acknowledged, which also point to opportunities for future research.

First, the study is based on observational data, which limits causal inference. While associations are identified, it is possible that more satisfied users are also more likely to recognise and mention personalised features. However, the robustness of the results across multiple specifications, combined with the distinction between functional and explicit recognition, suggests that the observed relationships reflect meaningful behavioural patterns rather than purely reverse causality. Future research could employ experimental or longitudinal designs to establish causal direction.

Second, the analysis is limited to the Indian market. While this context provides valuable insights into an emerging economy where e-commerce adoption has expanded rapidly, generalisability to other markets remains uncertain. Future studies should examine cross-cultural differences in AI awareness and consumer response across different levels of AI familiarity, digital literacy, and trust in technology.

Third, the sentiment analysis relies on the VADER lexicon, which was designed for standard English text and may not fully capture linguistic nuances such as code-switching or informal expressions common in Indian reviews (e.g., Hinglish). This limitation may explain the divergence observed between positive sentiment (mean = 0.235) and low ratings (mean = 2.43). Developing context-specific and language-specific sentiment models would improve measurement accuracy.

Fourth, the AI awareness measure captures the presence of relevant terms but does not distinguish between positive and negative references to AI. A review stating the algorithm gave terrible recommendations would receive the same AI awareness score as a review stating the recommendations were excellent. Future research could incorporate context-sensitive sentiment analysis specific to AI mentions to differentiate between favourable and unfavourable references.

Fifth, loyalty is inferred from review content rather than directly observed behaviour. While this approach captures authentic consumer expression and avoids the limitations of survey-based measures, it does not measure actual repurchase behaviour over time. Future research could integrate review-based analysis with transactional data to examine whether AI awareness predicts repeat purchases.

Finally, the dataset is unbalanced across platforms, with Amazon India contributing 99,000 reviews and Flipkart only 18,000. While application-level fixed effects were included to control for this imbalance, more balanced samples would allow for more precise platform comparisons and interaction effects.

6. CONCLUSION

6.1 Summary of the Study

This study examined whether consumer recognition of AI-enabled personalisation is associated with e-commerce loyalty, drawing on the Stimulus-Organism-Response (SOR) framework and the Technology Acceptance Model (TAM). Using a large-scale dataset of 189,000 user reviews from four major Indian e-commerce platforms Flipkart, Amazon India, Myntra, and Meesho, the study applied text mining and sentiment analysis (VADER) to capture behavioural expressions of consumer experience.

The findings are based on observed statistical associations and should be interpreted as indicative of behavioural patterns rather than causal relationships.

The results indicate that consumer AI awareness is positively associated with app ratings ($\beta = 0.0277$, $p < 0.001$). This relationship holds across both functional expressions (e.g., "recommend") and explicit technological references (e.g., "algorithm"), with no statistically significant difference between the two forms of awareness. Recognition of value appears to be associated with evaluation outcomes. In addition, perceived usefulness, proxied through sentiment, is positively associated with ratings ($\beta = 0.0252$, $p < 0.001$) and partially explains how review content translates into overall evaluations ($\Delta R^2 = 0.024$, $p < 0.001$). Platform-level differences were also observed, with Meesho showing a significantly higher rating effect ($\beta = 0.354$, $p < 0.001$) compared to Flipkart, Amazon India, and Myntra.

6.2 Theoretical Contributions

This study contributes to the literature in three key ways.

First, it introduces consumer AI awareness as a measurable behavioural construct within digital commerce. By demonstrating that awareness can be identified through natural language using a comprehensive 24-term regex dictionary and linked to observable outcomes, the study extends existing research beyond system-level and survey-based approaches. This extends the SOR framework by showing that algorithmic stimuli influence responses not only through internal evaluation but also through conscious recognition. Where such recognition is present in reviews, loyalty responses are higher.

Second, the finding that functional and explicit awareness produce comparable effects refines signalling theory in AI-mediated contexts. The findings suggest that perceived usefulness signals may be as effective as technological signals in shaping consumer evaluations. What may matter is not whether consumers recognise the technology itself, but whether they perceive value in the outcomes it produces.

Third, the study provides empirical support for TAM's core proposition in large-scale, behaviour-based settings. Perceived usefulness, captured through sentiment, remains a significant predictor of evaluation outcomes and operates as a mechanism linking experience to behavioural responses.

6.3 Managerial Implications

The findings offer several actionable implications for practice.

First, e-commerce platforms should prioritise the perceived usefulness of AI-driven features over their technological visibility. The results indicate that consumers respond positively when personalised assistance is helpful, regardless of whether it is explicitly recognised as AI. Enhancing recommendation relevance and decision support is likely to be more effective than emphasising algorithmic sophistication. When customers explicitly acknowledge useful recommendations, such recognition is associated with higher evaluation outcomes.

Second, communication strategies should focus on intuitive and user-friendly language. Functional expressions such as "recommended for you" appear sufficient to generate positive evaluations. Everyday expressions such as "recommend" exhibit comparable associations with ratings as technical terms such as "algorithm".

Third, consumer language can serve as a diagnostic tool. Monitoring the presence of recommendation-related expressions in reviews can help assess whether personalisation features are being noticed and valued. Declines in such expressions may indicate reduced effectiveness of recommendation systems.

Fourth, platform-specific strategies may be required. The observed variation across platforms suggests that the effectiveness of personalisation may vary across platform types. The positive coefficient observed for Meesho may indicate platform-level differences.

Finally, the overall rating distribution (mean = 2.43, SD = 1.72) indicates that user evaluations are skewed towards lower ratings. While AI awareness and perceived usefulness are positively associated with evaluations, their effects are modest in magnitude. Broader service quality factors remain critical for improving overall satisfaction.

6.4 Concluding Remarks

This study provides evidence that consumer recognition of AI-enabled personalisation is associated with higher evaluation outcomes in e-commerce contexts. Based on the analysis of 189,000 user reviews from four leading Indian shopping applications, the findings show that AI awareness is positively associated with app ratings ($\beta = 0.0277$, $p < 0.001$), that this relationship holds across both functional and explicit forms of awareness, and that perceived usefulness serves as a key mediating mechanism.

Overall, the results suggest that consumers respond primarily to the value generated by AI-driven features rather than to the technology itself. Reviews containing recognition of helpful AI are associated with higher ratings. Everyday expressions such as "recommend" exhibit comparable associations with ratings as technical terms such as "algorithm". This highlights the importance of designing AI systems that enhance user experience in meaningful and noticeable ways.

As AI continues to shape digital marketplaces, understanding how consumers perceive and respond to algorithmic assistance remains an important research agenda. By introducing consumer AI awareness as a behavioural construct, providing large-scale empirical evidence from an emerging market, and offering practical guidance for e-commerce managers, this study provides a foundation for future research in this area.

Declaration

On behalf of all authors, the corresponding author states that there is no conflict of interest.

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work the author(s) used Grammarly and ChatGPT to assist with language refinement and readability improvement. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the published article.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

REFERENCES

Bhojwani, R., Paul, J. and Srivastava, R. (2026), "Role of artificial intelligence on consumer buying behavior: the dual effects of AI-enabled features on decision-making and trust", Journal of Research in Interactive Marketing, Vol. ahead-of-print No. ahead-of-print, doi: 10.1108/JRIM-11-2025-0702

Castelo, N., Bos, M. W., & Lehmann, D. R. (2019). Task-dependent algorithm aversion. *Journal of Marketing Research*, 56(5), 809-825. https://doi.org/10.1177/0022243719851788

Davenport, T., Guha, A., Grewal, D., & Bressgott, T. (2020). How artificial intelligence will change the future of marketing. *Journal of the Academy of Marketing Science*, 48(1), 24-42. https://doi.org/10.1007/s11747-019-00696-0

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319-340. https://doi.org/10.2307/249008

De Keyser, A., Köcher, S., Alkire, L., Verbeeck, C., & Kandampully, J. (2019). Frontline service technology infusion: conceptual archetypes and future research directions. Journal of Service Management, 30(1), 156-183. https://doi.org/10.1108/JOSM-03-2018-0082

Dick, A. S., & Basu, K. (1994). Customer loyalty: Toward an integrated conceptual framework. *Journal of the Academy of Marketing Science*, 22(2), 99-113. https://doi.org/10.1177/0092070394222001

Dietvorst, B. J., Simmons, J. P., & Massey, C. (2015). Algorithm aversion. *Journal of Experimental Psychology: General*, 144(1), 114-126. https://doi.org/10.1037/xge0000033

Dumlao, J. (2024). *ShoppingAppReviews dataset* [Data set]. Kaggle. https://www.kaggle.com/datasets/jocelyndumlao/shoppingappreviews-dataset

Grewal, D., Hulland, J., Kopalle, P. K. and Karahanna, E. (2020), "The future of technology and marketing: a multidisciplinary perspective", Journal of the Academy of Marketing Science, Vol. 48 No. 1, pp. 1-8, doi: 10.1007/s11747-019-00711-4

Hennig-Thurau, T., Gwinner, K. P., Walsh, G., & Gremler, D. D. (2004). Electronic word-of-mouth via consumer-opinion platforms: What motivates consumers to articulate themselves on the Internet? *Journal of Interactive Marketing*, 18(1), 38-52. https://doi.org/10.1002/dir.10073

Hermann, E., & Puntoni, S. (2024). Artificial intelligence and consumer behavior: From predictive to generative AI. *Journal of Business Research*, 180, Article 114720. https://doi.org/10.1016/j.jbusres.2024.114720

Kshetri, N. (2018). The emerging role of big data in key development issues: Opportunities, challenges, and concerns. *Big Data & Society*, 5(2), 1-14. https://doi.org/10.1177/2053951714564227

Komiak, S. Y. X., & Benbasat, I. (2006). The effects of personalization and familiarity on trust and adoption of recommendation agents. *MIS Quarterly*, 30(4), 941-960. https://doi.org/10.2307/25148760

Lankton, N., McKnight, D. H. and Thatcher, J. B. (2015), "Incorporating trust-in-technology into expectation disconfirmation theory", Journal of Strategic Information Systems, Vol. 24 No. 2, pp. 128-45, doi: 10.1016/j.jsis.2014.11.001.

Logg, J. M., Minson, J. A., & Moore, D. A. (2019). Algorithm appreciation: People prefer algorithmic to human judgment. *Organizational Behavior and Human Decision Processes*, 151, 90-103. https://doi.org/10.1016/j.obhdp.2018.12.005

Longoni, C., Bonezzi, A., & Morewedge, C. K. (2019). Resistance to medical artificial intelligence. Journal of Consumer Research, 46(4), 629-650. https://doi.org/10.1093/jcr/ucz013

McKnight, D. H., Choudhury, V., & Kacmar, C. (2002). Developing and validating trust measures for e-commerce: An integrative typology. *Information Systems Research*, 13(3), 334-359. https://doi.org/10.1287/isre.13.3.334.81

Mehrabian, A., & Russell, J. A. (1974). *An approach to environmental psychology*. MIT Press.

Puntoni, S., Reczek, R. W., Giesler, M. and Botti, S. (2021), "Consumers and artificial intelligence: an experiential perspective", Journal of Marketing, Vol. 85 No. 1, pp. 131-51, doi: 10.1177/0022242920953847.

Ribeiro, A., Rivero, A. J. L. and Abrantes, J. L. (2025), "The impact of artificial intelligence on consumer behavior towards brands: a systematic review", Electronic Commerce Research, Advance online publication, doi: 10.1007/s10660-025-10063-7.

Spence, M. (1973). Job market signaling. Quarterly Journal of Economics, 87(3), 355-374. https://doi.org/10.2307/1882010

Tam, K. Y., & Ho, S. Y. (2006). Understanding the impact of web personalization on user information processing and decision outcomes. *MIS Quarterly*, 30(4), 865-890. https://doi.org/10.2307/25148757

Zhao, L., Chen, Z. and Wang, Y. (2025), "Automated interactions, authentic bonds? AI disclosure, consumer perceptions and loyalty dynamics on social media platforms", Journal of Research in Interactive Marketing, Vol. ahead-of-print No. ahead-of-print, doi: 10.1108/JRIM-06-2025-0306.