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AI-Driven Consumer Analysis for Designing Promotional Strategies for Online Shopping of Electronic Goods: A Dual Theory Approach

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Abstract: **The fast growth of Artificial Intelligence (AI) in e-commerce has transformed the way consumer behaviour is analysed by retailers and created new challenges to develop effective promotional strategy. This study investigates consumer preference of AI based recommendation while shopping through online of electronic goods by surveying 284 consumers. The analysis finds that younger consumers prefer strongly AI-driven recommendations while shopping, however perceived risk associated with online shopping does not decrease with use of AI. Further, an examination of consumer reviews collected from the Amazon platform during the Deepavali festival for iPhone. The findings reveal that consumer reviews are predominantly on price sensitivity, quality of service, delivery experience, and prestige of brand. These insights help online retailers to design customized promotional strategy to enhance purchase intention of consumers. Overall, the study contributes to present literature on online shopping by offering a novel approach to develop technique of promotions.**

Keywords: **Artificial Intelligence, Consumer Review, Sentimental Analysis, Promotional Strategy.**

1. INTRODUCTION

This study investigates how to utilise AI-based recommendation and reviews of consumer to build effective promotional strategies for online electronic goods to retailers. Past study has examined how recommendation of AI system can help to understand behaviour and improve decision-making to retailers (Huang & Rust, 2020). Moreover, current study focuses on a positive relationship between the use of recommendation of AI and purchase intention of AI. For example, Lalicic & Weismayer, (2021), found that when AI tools suggest products by customise product according to their preferences purchase more.

However, even though these researchers examine the impact of AI on particular consumer behaviours or overall purchase intentions (Patil, n.d. (Konuk, 2019), there is a notable gap in the literature regarding how online retailers can proactively use AI-based consumer behaviour analysis-especially review analysis, for effective promotional strategies. In particular, limited research addresses how focuses on AI-driven insights can be translated into specific promotional strategies that increase marketing campaigns; decrease perceived risk, and increase customer engagement in real time (Ta et al., 2024). The effectiveness of these promotional tools varies, with strategies such as “buy one get one free” proving effective in driving consumer engagement and sales (Gordon-Hecker et al., 2020). In this context, artificial intelligence tools- like recommendation systems, personalised offers, and automated customer support- have a significant impact on consumer behaviour and promotional impact (Zhang & Xiong, 2024) (Gao & Liu, 2022). AI algorithms can hold the capacity by purchase history, product preferences, and browsing behaviour and while also automatically assembling personalised offers and promotional strategies (Mustak et al., 2024).

Evaluation of consumers significantly contributes to analysing behaviour by giving valuable insights into emotional responses, individual preferences, and purchase intention (Malik & Bilal, 2024; Fernandes et al., 2022). By employing data from reviews, businesses can customise their marketing strategies and enhance them. By using a review of consumer data, enterprises can tailor their marketing and enhance customer experiences (Sun et al., 2025). Reviews reveal specific product features that consumer prefer, allowing companies to adjust their offerings accordingly. Sentimental analysis of reviews helps in revealing emotional tendency toward products, which can further guide development of product and promotional strategies (Zhong et al., n.d.)

This study applies two theoretical frameworks to examine the manner in which AI-driven consumer behaviour analysis can influence promotional strategies. Initially, Consumption Value Theory explains why consumers do decisions of purchase decisions based on various value dimensions- emotional, social, functional, epistemic, and conditional (Sheth et al., 1991). This theory is particularly significant in e-commerce, where promotions must appeal to diverse consumer motivations. Second, Signaling Theory posits that consumers depend on observable indicators to deduce credibility, quality, and trust in scenarios characterised by information asymmetry (Spence, 1978 ; Kirmani & Rao, 2000). Within digital marketplaces, AI-generated recommendations serve as trust signals, effectively communicating retailer competence, data-driven personalisation, and product relevance.

Previous research on AI-assisted consumer behaviour analysis has largely emphasised exhibiting trends and preference identification (Bilal et al., 2024) (Wang, 2025). This study distinguishes itself by analysing 1,020 iPhone consumer reviews from Amazon using sentiment analysis to generate promotional strategy insights. Google Gemini is used to analyse data and generate a Promotional strategy based on consumer behavioural trends and consumer emotions.

The findings indicate that consumers who consider AI recommendations have an increased frequency of shopping. AI gives product suggestions based on the purchase patterns of previous customers, and consumer doubts are solved instantly, often through the support of chatbots. These results show that AI increases sentimental value and convenience, supporting the Consumption Value Theory. However, AI recommendations did not reduce the risks associated with online shopping, like product authenticity, fraud, or delivery issues. Because AI cannot give security guarantees, consumers perceive risk associated with it. The research also identifies the factors consumers prefer when online shopping: first, discounts/offers are the strongest influencer, next, consumer reviews, price, brand reputation, and lastly, warranty and returns. The AI-based promotional strategy generated from the reviews of consumers include examples such as:

“iPhone — Great Camera, Fast Delivery — Official Seller + Easy Returns.”

“Worried about service? 30-day return & verified support included.”

This study contributes to the present existing literature by demonstrating in online shopping contexts, how AI analysis of behaviour of consumer can inform the design of promotional strategies, specifically for electronic products. Supporting with previous researches, this research investigate the influence of AI recommendations on frequency of shopping, perceived risk, and saving of time. Additionally, it also offers two important contributions: (1) it targets on the growing trend of use of AI recommendation in shopping of electronic product, because consumer evaluate multiple factors in a high-involvement category products while shopping and (2) it analyses reviews consumer in the festival season to know how consumers responded to activities of promotion. This gives retailers with insights into both expectations of consumer and actual effectiveness of their promotional campaigns.

(1) to assess the influence of AI recommendations on consumers’ perceived risk, (2) to examine the relationship between AI recommendations and purchase-related behavior, and (3) to demonstrate how AI-based sentiment analysis of consumer reviews can be used to develop effective promotional strategies. By focusing on electronic goods, this research extends existing AI and marketing literature to a high-risk, high-value product context.

2. LITERATURE REVIEW

AI plays a crucial role in consumer behaviour analysis, primarily, altering how organisations understand, anticipate and interact with customers. By analysing data of individual customers, it can deliver highly tailored experiences, including customised recommendations of products (e.g. Amazon, Netflix), tailored marketing communications and content optimised pricing and offers according to individual purchasing tendencies. Previous research in the relation between consumer behaviour and AI focused on enhanced accuracy of demand forecasting and identification of high-value customers and history of purchase, browsing behaviour, and demographic data to customise the product offerings and marketing communication (Praveen Kumar et al., 2024; Hasan et al., 2025), thereby enhancing customer engagement and increasing purchase intention due to perceived relevance .(Asante & Jiang, 2023), (Gupta & Khan, n.d.). Improved customer satisfaction is achieved through streamlined, accessible, and personalised service (Singh & Singh, 2024)

Consumer Value theory explains that consumers engage in purchasing decisions based on their perceived value of services or products. This value is primarily conceptualised as a trade-off: the total benefits a customer receives versus the total sacrifices (costs) they made.

The second theoretical framework discussed in Signaling Theory, originally proposed by Michael Spence (Spence, 1978) , proposes the mechanisms by which proposes the processes through which one entity conveys credible information to another in contexts marked by information asymmetry- particularly when consumers do not have exhaustive knowledge regarding a product or service before making a purchase. A retailer that includes AI-driven personalisation systems or acquires sustainability certifications communicates a robust technological signal, leadership and credibility, consequently mitigating perceived risk. Further retailers also implement cutting-edge technologies such as AI augmented reality/virtual reality, and chatbots as modern indicators, customer-centricity, and reliability, which consumers interpret as quality makers, prestige and competence. Similarly, positive customer reviews function as social signals of product credibility and reliability, where a significant volume of authentic reviews helps in reducing uncertainty in purchase (Filieri et al., 2020) Additionally, elements like the ability of AI to explain, responsiveness and transparency act as significant signals of a reliable system and utilisation of ethics, exerting a significant impact on consumers' trust and their inclination to adopt AI-driven services.

The combination of Consumer Value Theory and Signaling Theory provides a cohesive theoretical framework that explains how AI recommendations impact on behaviour of consumers across all proposed hypotheses. Consumer Value Theory indicates that AI systems increase a consumer's internal examination of value by offering highly relevant product recommendations, developing convenience, decreasing decision effort, and enhancing overall benefits related to perceived costs. Simultaneously, Signaling Theory explains that AI-driven recommendations act as outer trust indicators that aid consumers in interpreting retailer credibility, product dependability and expertise, mainly in situations characterised by high uncertainty. When these two theories work together, the recommendation of AI enhances perceived value and decreases information asymmetry, promoting consumers to feel high confidence and decrease risk while online purchasing.

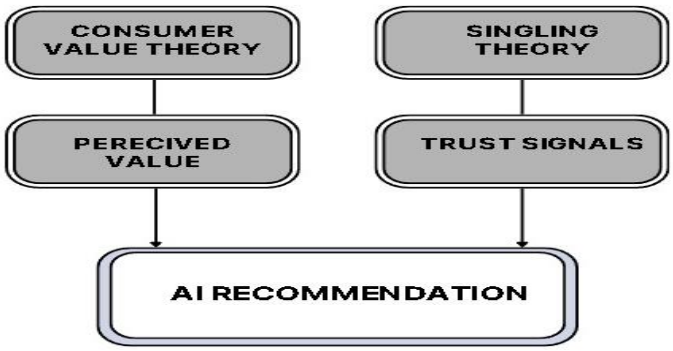


Figure 1: Conceptual Theoretical Model

3. HYPOTHESES DEVELOPMENT

3.1 Risk decrease by influence of AI recommendation

It's become crucial in e-commerce research and online marketing to understand how consumers view, trust, and adopt AI-driven systems. Norberg et al., (2007) first focused on the "privacy paradox", showing that due to contextual trust and perceived benefits, frequency of consumers to share personal information online than state their privacy concern. Dabholkar & Sheng, (2012) found that perceived risk significantly diminishes the trust and quality of communication, affecting loyalty toward voice-controlled AI devices like Siri. Similarly, Shi et al. (2020) examined using dual-process theory in travel planning, found that systematic (fact-based) cues foster stronger adoption than heuristic ones, with cognitive trust in high-risk situations and social trust prevailing in low-risk contexts.

Recent research expands this understanding into newer AI environment. Al Murshidi et al., (2024) found that among UAE students, awareness of both the benefits and risks of ChatGPT found that among UAE students, awareness of both the advantages and risks of ChatGPT enhanced their intention to use it-applying that transparency about AI limitations can actually fostering adoption. Combining these studies reveal that a dynamic interplay of trust, perceived risk, emotional engagement, and contextual significance influenced by adoption of AI and purchase intention, underscoring the need for transparent, trustworthy, and adaptive AI systems in digital commerce.

H1: *The influence of AI recommendations adversely affects perceived risk of consumer toward online purchases.*

3.2 AI recommendation and consumer purchase intention

Research on AI implementation and purchase intention highlights multiple influencing factors. Hostler et al., 2011 found that recommendation agents enhance search effectiveness, satisfaction, and impulse buying. Dabholkar & Sheng, (2012) investigated that higher consumer involvement with RAs strengthens trust and purchase intention, though financial risk can weaken this effect. Baek et al., (2012) emphasized review quality and credibility in shaping buying decisions. Pantano et al., 2019 and Konuk, (2019) showed perceived innovativeness with trust, loyalty, and purchase behavior. Concerns about transparency and ethics were raised by Khrais, 2020, stressing Explainable AI, while Schmidt et al., (2020) warned that excessive transparency may reduce trust. Using TRAM, Pillai et al., (2020) found enjoyment, personalization, and interactivity increase shopping intention. Qin et al., (2022) showed human–AI collaboration enhances service quality and purchase intent. Recent studies such as Nazir et al., (2023) and Bunea et al., (2024) confirm that AI-driven engagement, perceived usefulness, and ease of use positively influence purchase intentions. However, privacy concerns and anxiety (e.g., Yin et al., 2025) may moderate this effect. Overall, the literature consistently supports the hypothesis that AI recommendations positively influence purchase intention, provided trust, relevance, and transparency are maintained.

H2: *Purchase intention is positively influenced by AI recommendation*

3.3 Sentimental analysis on consumer reviews to develop promotional strategy

Research on reviews of online consumer feedback and purchase intention has evolved significantly over the years. Forman showed that revealing reviewer identities and sharing geographical data on Amazon increase perceived helpfulness and boost sales, highlighting the social dimensions of online Word-of-mouth communication. Benlian et al. (2012) indicated that provider cues enhance perceived usefulness, while consumer reviews build trust and emotional connections, especially for experience goods. Baek et al. (2012) proved that peripheral cues such as reviewer credibility and central cues such as review content affect perceived helpfulness depending on reader objectives. Sutanto & Aprianingsih (2016) found that quality, credibility, quantity, and sentimental reviews are key factors in increasing purchase intention.

Eftimov (n.d.) discovered that purchasing decisions and trust are built through online reviews while stressing the need to identify fraudulent reviews. T. Chen et al. (n.d.) illustrated that consumers, particularly females, pay close attention to negative reviews, and Filieri et al. (2020) found that extremely negative ratings are considered more helpful for high-quality products. Bounie et al. (n.d.) revealed that online peer reviews influence purchasing decisions similarly to expert assessments. Cho et al. (2021) showed that star ratings and sentiment work together to influence demand and described online reviews as “free sales assistants.” Changchit et al. (2022) found that online reviews act as alternatives for physical product experiences and increase purchase confidence. Kothari planned a sentiment analysis model for e-commerce platforms to provide actionable insights into customer emotions. Overall, online reviews influence consumer trust, product assessment, and purchase intentions, and insights from sentiment analysis can guide personalisation, sentiment management, and strategic adaptability in digital commerce.

H3: Insights from sentiment analysis of reviews of consumers can be used to data-driven promotional strategies that enhance the effectiveness of AI recommendations.

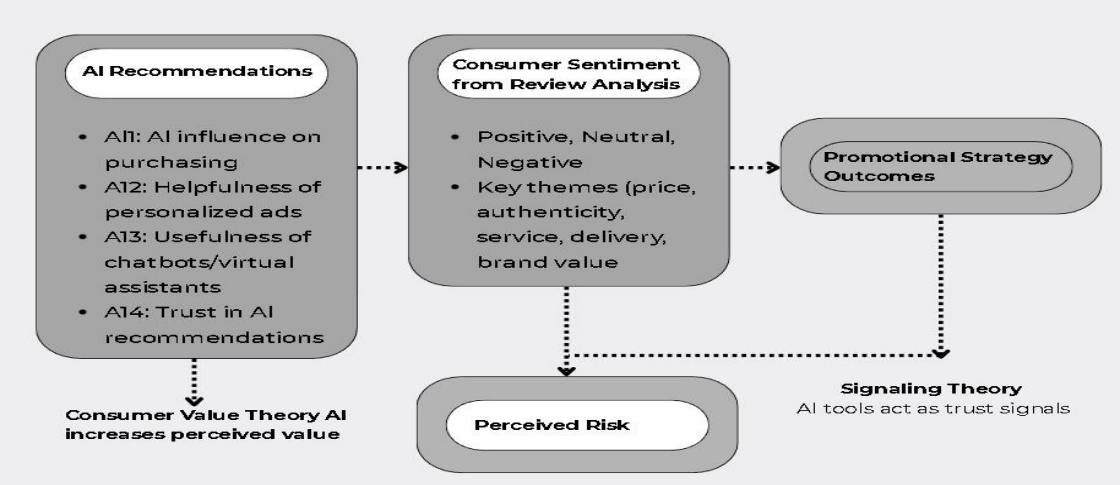


Figure 2: AI driven Consumer Behaviour Analysis and Promotional Strategy Framework

4. DATA AND METHODOLOGY

4.1 Sample and data

The aim of this study is to analyse reviews of consumer to study their behaviour and, on the basis of findings, form an effective promotional strategy. A quantitative correlational research method is applied to investigate the relationships between variables.

4.2 Data Gathering Procedure

Primarily, data were collected from 286 respondents aged 18 to 25 years by a survey. The survey is conducted to understand the impact of AI recommendations on their buying decisions and intentions. A Google Form was distributed to collect responses. Next, reviews of consumers collected during the festival season from Amazon regarding iPhone sales. A total of 1,280 reviews were analysed to help in customising from relevant literature to identify both statistical and economic relationships.

4.3 Statistical Treatment of Data

The research applied a correlational descriptive and regression method. This method helps to examine the association between the variable in the descriptive data. For the qualitative dataset, sentiment analysis was conducted using Natural Language Processing (NLP) techniques. To get insights and suggestions for promotional strategies sentimental analysis results were uploaded to ChatGPT.

5. RESULTS AND DISCUSSION

H1: *Perceived risk of consumers toward online purchases is adversely affected by the influence of AI recommendations.*

Table 1: Results of ANOVA

ANOVA[a]					
Model		df	Mean Square	F	Sig.
Regression	11.087	1	11.087	1.107	.294[b]
Residual	2764.913	276	10.018		
Total	2776	277			

a. Dependent Variable: totalrp

b. b. Predictors: (Constant), AI1

The analysis of ANOVA shows an F-value of 1.107 and a p-value of .294 which exceeds the standard significance level of 0.05. this reveal that the regression model lacks statistical significance.

Table 2: Results of Correlations

Correlations			
		totalrp	AI1
Pearson Correlation	Totalrp	1	0.063
	AI1	0.063	1
Sig. (1-tailed)	Totalrp	.	0.147
	AI1	0.147	.
N	Totalrp	278	278
	AI1	278	278

The analysis examined whether AI-based recommendations (AI1) could remarkably influence total risk perception (totalrp). The results of the regression showed a very weak relationship between the two variables. The model's R value (.063) shows almost no linear correlation, and R2 (.004) reveals that only 0.4% of the variation in total risk perception is accounted for by AI1. The Adjusted R2 (.000) further confirms the model's lack of explanatory power.

Table 3: Results of Regression Analysis

Model Summary[b]									
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.063[a]	0.004	0	3.16509	0.004	1.107	1	276	0.294
a. Predictors: (Constant), AI1									
b. Dependent Variable: totalrp									

With a Pearson correlation coefficient of .063 and a p-value of .147 (1-tailed) the correlation analysis also supports these findings. This suggests a very weak, very small positive relationship between AI1 and totalrp.

Table 4: Results of Hypothesis

Hypothesis	Statement	Decision
H1	The influence of AI recommendations adversely affects consumers' perceived risk toward online purchases.	Not Supported
H2	Purchase intention is positively influenced by AI recommendations.	Supported
H3	Sentiment-analysis insights from consumer reviews can be used to develop data-driven promotional strategies.	Supported

In conclusion, the study found that the AI recommendations and total risk perception no significant linear relationship. Participants' perceptions of risk in online shopping are not significantly influenced by the effect of AI-based recommendations impact their purchase decisions.

H2: *Purchase intention is positively influenced by AI recommendation*

Table 5: Results of Correlation

How often do you shop online			AI1	AI2	AI3	AI4
Howoftendoyoushoponline	Pearson Correlation	1				
	Sig. (2-tailed)					
	N	284				
AI1	Pearson Correlation	.289**	1			
	Sig. (2-tailed)	0				
	N	284	284			
AI2	Pearson Correlation	.229**	.843**	1		
	Sig. (2-tailed)	0	0			
	N	284	284	284		
AI3	Pearson Correlation	.178**	.765**	.886**	1	
	Sig. (2-tailed)	0.003	0	0		
	N	284	284	284	284	
AI4	Pearson Correlation	.198**	.757**	.701**	.860**	1
	Sig. (2-tailed)	0.001	0	0	0	
	N	284	284	284	284	284

The correlation analysis explored relationships among **shopping frequency** and four **AI-related perceptions** — influence of AI recommendations (AI1), helpfulness of personalized ads (AI2), chatbot/virtual assistant usefulness (AI3), and trust in AI recommendations (AI4) — using data from 284 respondents.

1. Relationship between Shopping Frequency and AI Variables:

All four AI variables show **weak to moderate positive correlations** with online shopping frequency, all **statistically significant at p < .01**. This means that individuals who shop online more frequently are also more likely to be influenced by AI recommendations (r = .289), find personalized ads helpful (r = .229), believe chatbots improve their experience (r = .178), and trust AI recommendations (r = .198).

2. Interrelationships among AI Perception Variables:

The correlations among AI1–AI4 are **strong to very strong (r=.701 to .886)** and all **highly significant (p < .001)**. This indicates that positive perceptions of one AI feature are strongly associated with positive perceptions of others. For example, users who find AI ads helpful (AI2) also tend to believe chatbots enhance shopping (AI3,r=.886) and trust AI recommendations (AI4,r=.701).

The findings suggest two major insights:

- **Higher engagement in online shopping** is associated with **greater acceptance and trust in AI tools**.
- **AI perceptions are interlinked**, showing a **"halo effect"**—a positive experience with one AI application (like chatbots) strengthens trust and acceptance of others (like recommendations and ads).

H3: ***Insights from sentiment analysis of consumer reviews can be used to develop data-driven promotional strategies that enhance the effectiveness of AI recommendations.***

Figure 3 Results of AI driven Consumer Sentiment and Promotion Strategy Framework

Sentiment Analysis Results

Total items analyzed: 1280 Positive: 524 items (40.9%) Neutral: 626 items (48.9%) Negative: 130 items (10.2%)

Table 6: Sentiment Distribution Analysis

Sentiment	Count	Percentage
Positive	524	40.90%
Neutral	626	48.90%
Negative 10.2	130	10.2

Key Themes Identified

• Customer service interactions • Value for money considerations

Actionable Improvement Customer satisfaction patterns Product/service quality feedback Delivery and shipping experiences

Suggestions

Enhance product quality based on feedback patterns

Improve customer service response times

Optimize delivery and shipping processes

• Address common customer concerns

• Implement feedback collection improvements

Key Insights from Data

Average Rating: **3.04 / 5** → Mixed perception; customers are polarized.

Distribution:

1★ & 2★ reviews (≈40%) → many dissatisfied buyers.

4★ & 5★ reviews (≈43%) → Strong positive group exists.

3★ reviews (17%) → Neutral, open to influence.

Helpful Reviews: Highly up voted reviews talk about: Smooth transition issues from Android → iPhone, Design & aesthetics appreciation, High price vs. value doubts Sales event satisfaction (e.g., Great Indian Sale deals)

Customer Pain Points

- Price sensitivity – Many feel its "waste of money" compared to Android.
- Return/refund hassle – Customers frustrated with return policies.
- Network/5G issues – Complaints about connectivity.
- Resale disappointment – Buyers mention poor resale experience.
- Confusion about authenticity – Some distrust in Amazon as a seller.

Customer Motivators

- Design & style appeal – Positive reviews highlight looks & colors.
- Brand prestige – "Owning an iPhone" is aspirational.
- Festival discounts – Buyers love big sale event deals.
- Photography & performance – Appreciated by positive reviewers.

Promotional Strategy Recommendations for Retailer

1. Target Segments Value-conscious buyers (3★– ratings) → Need reassurance on price, EMI, trade-in benefits.

Aspirational buyers (4★ & 5★ ratings) → Already positive; reinforce brand prestige.

2. Promotions: Bundle offers: Free accessories (cases, screen protectors, AirPods discounts).

Exchange/upgrade schemes: Highlight trade-in value to counter resale worries.

EMI & cashback plans: Target middle-income aspirational buyers.

Festival sales campaigns: Push deals during Diwali, Big Billion Days, and Great Indian Sale.

3. Messaging

Address pain points:

Promote easy return & replacement policy.

Guarantee genuine products with warranty.

Highlight motivators:

Showcase design & lifestyle appeal in ads.

Share real customer testimonials with photos.

4. After-Sales & Loyalty

- 24/7 support assistance to reduce frustration.
- Loyalty programs – discounts for repeat buyers.
- Encourage review sharing with images (boosts trust).

AI recommendation

Tailored promotional strategy (practical & prioritized)

Below is a prioritized set of actions to (A) stop further damage to brand perception, (B) improve conversion, and (C) increase positive reviews.

3) Messaging & advertising (ad copy and targeting)

Top-targeting angle(s): highlight camera/battery + "official/verified seller" + simple returns policy. Example ad headlines:

"iPhone — Great Camera, Fast Delivery — Official Seller + Easy Returns"

"Worried about service? 30-day return & verified support included."

Audience segmentation:

Past Apple buyers / iPhone-interested audience's ➜ emphasize specs and ecosystem benefits.

Price-conscious / bargain audiences ➜ emphasize value, warranty & verified seller assurance.

Creative: use real customer photos (with permission) and short customer-quote overlays: "Battery lasted all day — Suresh, Bangalore".

4) Social proof & listing optimization

Pin a helpful positive review at top of Q&A or use "featured review" content on product page. **Use comparison tables** (if allowed) to emphasize advantages vs common competitors (battery, camera, price).

6. DISCUSSIONS

The research findings offer a detailed understanding of the behaviour of consumers in online shopping, focusing on the combined crucial value and trust alongside the developing role of AI. Offers/Discounts and customer reviews are identified as the important factor indicating consumers' choices of platform, moderately Brand Reputation and Price, yet equally influential. A significant observation is the pattern of multi-criteria decision-making, where shoppers weigh combinations of attributes.

Consumer acceptance of Ai is largely positive, with a substantial 91.2% of participants accepted that AI-driven recommendations save time and increase decision-making efficiency. This strong support reinforces the view that AI serves as valuable tool for convenience. Nonetheless, the study did not covered a significant relationship between the influence of AI recommendations and perceived risk of consumers' (h1 was not supported, p-.294). this implies that while AI may affect what a consumer purchase and speed, it does not automatically mitigate their sense of risk in the online environment, which is likely more influenced by traditional factors like brand reputation and return policies.

In contrast to the perceived risk results, the study confirmed H2, showing that a favourable view of AI characteristics is strongly associated with increased shopping frequency and intention of purchase. All four AI-related variables (AI influence, personalised ads, chatbots effectiveness, and trust in AI) exhibited significant positive correlations with the frequency of online shopping (r=.178=.289, p<.01). Additionally strong inter-correlations among the various AI variables (r=.701-.889) indicates a "halo effect" is at play; a positive experience with on AI feature (e.g., an efficient chatbots) increases the consumer's perception, acceptance, and trust in the platform's other AI tools (e.g. recommendations).

7. CONCLUSION

This research contributes to the expanding literature on AI in online retailing by showing how AI-based analysis of reviews of consumer reviews can be used to design targeted promotional strategies for electronic goods. Although recommendations of AI increase shopping frequency and convenience, they do not sufficiently combine perceived risk, suggesting that strong promotional strategies must merge with AI-driven personalisation with clear trust-building signals. By integrating Consumption Value Theory and Signaling Theory, the findings give a robust theoretical framework for understanding how AI impacts consumers' behaviours and communication for retailer effectiveness.

The results are helpful for practical implications to online retailers, highlighting the significance of risk-reducing features, the need to establish sentiment-based insights into promotional strategy, and are utilised to customise messaging by an AI tool. Future research could develop this work by investigating cross-category differences or using experimental designs to examine the influence of AI-informed promotional strategies.

Study Limitations and Future Research

The limitations of the study include a sample size of 284, the challenges include self-reported data and limited explanatory power of the regression model H1 with R^2 0.004 and a cross-sectional design. This suggests that the perception of risk is

significantly influenced by other unmeasured variables. So, studies in future should apply add expanded variables to moderating or mediating models, for example, trust, privacy concerns, and product complexity, to gain a deeper understanding of AI's full effect on perception. Moreover, an experimental study is also needed to apply causality and track evolving attitudes of consumers toward AI over time. Lastly, expanding the research framework to cross-cultural comparisons and product diversity will aid in investigating the robustness and generalising the present findings.

Practical and Strategic Implications

The results were evidence of practical application for e-commerce strategies. This gives significance to discounts and reviews, retail platforms should adopt trust-building and strategies to create value by focusing on transparent pricing, ensuring the credit to genuine reviews of customers, and increasing AI systems to give personalised, efficient suggestions. Since perceived risk did not decrease with AI, returns or exchanges need to engage with customer concerns by offering guaranteed hassle-free returns by online retailers, by providing detailed warranty information, and prominently showing "verified seller" badges. Sentiment analysis offers valuable insights for data-driven marketing tactics, with a mixed consumer response with 40.9% positive, 48.9% neutral and 10.2% negative. Online platforms to strengthen purchasing incentives and to address issues such as return difficulties, like festive discounts and attractive designs, use this information to swiftly address negative feedback and tailor promotions.

Table 7: Overview of Names of variable and Codes

Variable Category	Variable Name	Code	Measurement Items (Examples)	Scale
Independent Variables (AI-Related Perceptions)	Influence of AI Recommendations	AI1	"AI recommendations influence my purchase decisions"	5-point Likert
	Helpfulness of Personalized Ads	AI2	"Personalized ads help me find products faster"	5-point Likert
	Usefulness of Chatbots / Virtual Assistants	AI3	"Chatbots improve my shopping experience"	5-point Likert
	Trust in AI Recommendations	AI4	"I trust the recommendations provided by AI systems"	5-point Likert
Mediating Variable	Consumer Sentiment (Review Analysis)	SENT	Positive, Neutral, Negative sentiment	Text → NLP sentiment score
Dependent Variables	Perceived Risk	RP	"I feel uncertainty when purchasing products online"	5-point Likert
	Purchase Intention / Shopping Frequency	PI / SF	"How often do you shop online?"	Frequency scale
Outcome Variable	Promotional Strategy Effectiveness	PSE	Data-driven strategy output based on sentiment	Derived variable

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