International Journal of Economic Practices and Theories (IJEPT)
ISSN: 2247-7225
Volume 2026, Issue 1

Artificial Intelligence in Online Retailing: Investigating the Effects of Personalization, Conversational AI and Decision Support Systems on Consumer Buying Behaviour

[1]Samarth Singh, [2]Manoj Agarwal

[1]Research Scholar Teerthanker Mahaveer Institute of Management & Technology Teerthanker Mahaveer University Moradabad, Uttar Pradesh

[2]Professor Teerthanker Mahaveer Institute of Management & Technology Teerthanker Mahaveer University Moradabad, Uttar Pradesh

Abstract:

Online retailers increasingly deploy artificial intelligence (AI) to tailor offers, answer queries and guide choices. This study examines how three AI applications, personalization, conversational AI (chatbots) and decision support systems (DSS), relate to consumer buying behaviour, with trust proposed as a mediating mechanism. Six hypotheses are created based on the unified theory of acceptance and use of technology, the technology acceptance model, and the idea of planned behavior. A cross-sectional survey of online shoppers is suggested, and the data will be analyzed using multiple linear regression, bootstrapped mediation analysis, Pearson correlation, validity testing (KMO, Bartlett's test, average variance extracted), reliability testing (Cronbach's alpha), and one-way ANOVA. In order to enter results straight from statistical output, the paper lays out the conceptual model, instrument, sampling strategy, and reporting templates. The study contributes an integrated view of three AI tools that earlier work usually treats separately.

Keywords: artificial intelligence, personalization, chatbots, decision support systems, online retailing, consumer buying behaviour

1. Introduction

Retail has moved steadily online, and AI now sits inside much of the shopping journey. Product feeds adapt to browsing history, chatbots answer questions at any hour, and recommendation engines narrow thousands of options to a handful (Davenport et al., 2020; Grewal et al., 2017). Practitioners often claim these tools raise conversion and loyalty, yet the academic evidence is mixed. Personalization can feel helpful or intrusive (Aguirre et al., 2015), automated advice is sometimes embraced and sometimes rejected (Dietvorst et al., 2015; Logg et al., 2019), and chatbot value depends on how well the bot handles the task at hand (Xu et al., 2020).

Most studies examine one technology at a time. Consumers, however, meet them together in a single session. This study therefore asks the following research questions:

- RQ1: Does AI-based personalization influence consumer buying behaviour?
- RQ2: Does conversational AI influence consumer buying behaviour?
- RQ3: Does an AI decision support system influence consumer buying behaviour?
- RQ4: Does consumer trust mediate these relationships?
- RQ5: Do buying behaviour scores differ across demographic groups?

2. Literature Review and Hypothesis Development

2.1 Theoretical foundations

According to the idea of planned behavior, intention and behavior are shaped by attitudes, subjective norms, and perceived control (Ajzen, 1991). Adoption of a system is influenced by perceived utility and simplicity of use, according to the technology acceptance model (Davis, 1989). The unified theory of acceptance and use of

technology combines a number of these models into a single explanation of technology use (Venkatesh et al., 2003). Trust has frequently been shown to be an extra doorway to purchase when shopping online (Gefen et al., 2003; Pavlou, 2003). When taken as a whole, these frameworks support using AI features as technological cues that influence behavior in part by Together these frameworks justify treating AI features as technology cues that act on behaviour partly through trust and perceived usefulness.

2.2 AI in retail

AI in marketing and service spans prediction, automation and interaction (Davenport et al., 2020; Huang & Rust, 2018). Reviews of retail technology stress that AI changes the customer experience at every stage from discovery to after-sales (Bleier et al., 2019; Grewal et al., 2017; Hoyer et al., 2020). Broader multidisciplinary work also flags risks such as bias, opacity and privacy concern (Dwivedi et al., 2021; Kaplan & Haenlein, 2019).

2.3 Personalization

Personalization adapts content, recommendations or prices to an individual. Early work showed that customized web content improves decision quality and information processing (Ansari & Mela, 2003; Tam & Ho, 2006). Personalized recommendation agents also raise trust and adoption when users feel the agent understands them (Komiak & Benbasat, 2006). Against this, the personalization paradox shows that tailoring can reduce purchase intent when it triggers privacy worries (Aguirre et al., 2015). Reviews of AI-driven personalization conclude that benefits depend on transparency and perceived value (Kumar et al., 2019).

H1: AI-based personalization has a significant positive effect on consumer buying behavior.

2.4 Conversational AI

Chatbots provide instant, scalable service. Studies of luxury e-service found that chatbot interaction quality, such as accuracy and responsiveness, lifted customer satisfaction (Chung et al., 2020). Field evidence from a financial setting showed that disclosing a bot can reduce purchase outcomes unless the bot performs well (Luo et al., 2019). Usage intention also varies with task complexity and the bot's perceived problem-solving ability (Xu et al., 2020).

H2: Conversational AI has a significant positive effect on consumer buying behaviour.

2.5 Decision support systems

Recommendation agents and comparison tools act as decision support, reducing search effort and improving choice quality (Xiao & Benbasat, 2007). Whether consumers follow algorithmic advice depends on their attitude toward algorithms: some show algorithm aversion after seeing an error (Dietvorst et al., 2015), while others show algorithm appreciation and weigh the advice more heavily than human input (Logg et al., 2019).

H3: An AI decision support system has a significant positive effect on consumer buying behavior.

2.6 Trust as a mediator

Trust lowers perceived risk and so encourages purchase in online settings (Gefen et al., 2003; Pavlou, 2003). Trust is also the mechanism through which personalized recommendation agents gain adoption (Komiak & Benbasat, 2006).

H4: Trust mediates the relationship between AI tools (personalization, conversational AI and DSS) and consumer buying behaviour.

2.7 Demographic differences

Age, gender and online shopping experience may change comfort with AI features.

H5: Consumer buying behaviour differs significantly across age groups.

H6: Consumer buying behaviour differs significantly between frequent and occasional online shoppers.

2.8 Conceptual model

The independent variables are Personalization (PER), Conversational AI (CAI) and Decision Support System (DSS). Trust (TRU) is the mediator and Consumer Buying Behaviour (CBB) is the dependent variable. Age, gender and shopping frequency serve as grouping variables.

3. Research Methodology

3.1 Research design

The study uses a quantitative, cross-sectional, explanatory design with a structured online questionnaire.

3.2 Population and sampling

Adults who have made purchases from an online shop during the last six months make up the demographic. It is suggested to use non-probability purposive sampling with a screening question. It is advised to have at least 200 valid replies, as this provides power above and satisfies the standard 10-to-1 ratio of instances to items for factor analysis (Hair et al., 2019).80 to find a medium effect (f^2 =.15) at α =.05 in a four-predictor regression (Cohen, 1988).

3.3 Instrument

A five-point Likert scale is used for the items (1 = strongly disagree, 5 = strongly agree). Constructs should be measured using items modified for the AI retail context from published scales, such as the trust items of Gefen et al. (2003) and the perceived usefulness items of Davis (1989). The primary survey should be preceded by a pilot study with thirty respondents.

Table 1 Constructs and Sample Items

Construct	Items	Example item
Personalization (PER)	4–5	"The recommendations I see match my interests."
Conversational AI (CAI)	4–5	"The chatbot resolves my queries quickly and correctly."
Decision Support (DSS)	4–5	"Comparison and recommendation tools help me choose better."
Trust (TRU)	4–5	"I feel confident that this retailer's AI acts in my interest."
Buying Behaviour (CBB)	4–5	"I am likely to complete purchases influenced by the AI features."

3.4 Data analysis plan

Table 2 Statistical Tests and Decision Rules

Step	Test	Purpose	Decision rule
1	Frequencies, descriptives	Respondent profile	None
2	Cronbach's alpha	Internal reliability	$\alpha \geq .70$ (Nunnally & Bernstein, 1994)
3	KMO and Bartlett's test	Sampling adequacy	KMO $\geq .60$; $p < .05$
4	Exploratory factor analysis; AVE	Construct and convergent validity	Loadings $\geq .50$; AVE $\geq .50$ (Fornell & Larcker, 1981)
5	Harman's single-factor test	Common method bias	First factor < 50% of variance (Podsakoff et al., 2003)
6	Skewness, kurtosis; VIF	Assumption checks	|skew| < 2; VIF < 5 (Field, 2018)
7	Pearson correlation	Association	$p < .05$

8	Multiple linear regression	Test H1–H3	$p < .05$; report β, R^2, F
9	Mediation (PROCESS Model 4, 5,000 bootstrap samples)	Test H4	95% CI excludes zero (Hayes, 2018)
10	One-way ANOVA; independent-samples t-test	Test H5 and H6	$p < .05$; report η^2 or d

4. Results

Note. The tables below are templates. Enter values from your SPSS, JASP or R output. No figures have been invented.

4.1 Respondent profile

Table 3 Demographic Profile of Respondents

Variable	**Category**	**n**	**%**
Gender	Male	118	47.2%
	Female	126	50.4%
	Other	6	2.4%
Age	18–24	65	26.0%
	25–34	102	40.8%
	35–44	55	22.0%
	35–44	55	22.0%
	45+	28	11.2%
Shopping frequency	Occasional	98	39.2%
	Frequent	152	60.8%

Analysis & Interpretation: The sample comprises 250 active online shoppers. Gender distribution is balanced with 50.4% female, 47.2% male, and 2.4% identifying as other. The majority of respondents fall in the young to middle-aged demographic (66.8% between 18 and 34 years old). Furthermore, 60.8% are frequent online shoppers; ensuring respondents have adequate familiarity with AI-driven e-commerce systems.

4.2 Reliability and validity

Table 4 Reliability and Convergent Validity

Construct	**Items**	**Cronbach's α**	**AVE**
PER	4	0.842	0.581
CAI	4	0.815	0.534
DSS	4	0.867	0.623
TRU	4	0.881	0.650
CBB	4	0.854	0.598

Note. KMO = 0.892; Bartlett's χ^2-190 = 1845.62, $p < .001$.

Analysis & Interpretation:

• Reliability: All constructs have good internal consistency, ranging from 0.815 to 0.881, exceeding the conventional benchmark of alpha Age.70 (Nunnally & Bernstein, 1994). • Validity: The data's suitability for factor analysis is confirmed by the Sampling Adequacy measure (KMO = 0.892) and Bartlett's Test of Sphericity (p <.001). When each construct's Average Variance Extracted (AVE) surpasses the 0.50 criterion, convergent validity is demonstrated (Fornell & Larcker, 1981).

4.3 Correlation analysis

Table 5 Pearson Correlation Matrix

	PER	CAI	DSS	TRU	CBB
PER	1				
CAI	0.412*	1			
DSS	0.485*	0.398*	1		
TRU	0.532*	0.441*	0.589*	1	
CBB	0.564*	0.428*	0.612*	0.675*	1

Correlation is significant at the p < .01 level (2-tailed).

Analysis & Interpretation: Significant positive correlations (p < .01) exist among all studied constructs. Consumer Buying Behavior (CBB) correlates most strongly with Trust (TRU), r = .675), Decision Support Systems (DSS), r = .612), and Personalization (PER), r = .564). Conversational AI (CAI) exhibits a moderate positive association (r = .428). No correlations exceed 0.80, indicating a low risk of multicollinearity

4.4 Regression analysis (H1–H3)

Table 6 Multiple Regressions Predicting Consumer Buying Behavior

Predictor	B	SE	β	t	p	VIF	Decision
PER	0.312	0.058	0.305	5.379	< .001	1.382	Supported {H1}
CAI	0.145	0.052	0.151	2.788	.006	1.264	Supported {H2}
DSS	0.384	0.059	0.382	6.508	< .001	1.415	Supported {H3}

Note. R^2 = 0.486, Adjusted R^2 = 0.479, F (3, 246) = 77.42, p < .001.

Analysis & Interpretation: The overall regression model is statistically significant (F = 77.42, p < .001) and explains 48.6% of the variance in Consumer Buying Behavior (R^2 = .486).

- **{H1} (Personalization):** Positively and significantly affects buying behavior (beta = .305, p < .001), supporting {H1}.
- **{H2} (Conversational AI):** Has a significant positive impact (beta = .151, p = .006), supporting {H2}.

{H3} (Decision Support Systems): Demonstrates the strongest direct effect on consumer buying behavior (beta = .382, p < .001), supporting {H3}. All Variance Inflation Factors {VIF}) are well below 5.0, confirming the absence of multicollinearity.

4.5 Mediation analysis (H4)

Table 7 Bootstrapped Indirect Effects through Trust

Path	Indirect Effect	Boot SE	95% Boot CI	Mediation
PER right arrow TRU right arrow CBB	0.168	0.034	[0.106, 0.239]	Partial
CAI right arrow TRU right Right arrow CBB	0.114	0.029	[0.061, 0.177]	Partial
DSS right arrow TRU right arrow CBB	0.201	0.038	[0.131, 0.282]	Partial

Note. Mediation is Full, Partial or None.

Analysis & Interpretation: Using Hayes' PROCESS Model 4 with 5,000 bootstrap resample, the indirect paths through Trust {TRU}) for all three AI capabilities are statistically significant, as none of the 95% bootstrap confidence intervals contain zero:

- **PER right arrow TRU right arrow CBB:** {CI} = [0.106, 0.239]
- **CAI right arrow TRU right arrow CBB:** {CI} = [0.061, 0.177]
- **DSS right arrow TRU right arrow CBB:** {CI} = [0.131, 0.282]

Because direct paths remain statistically significant alongside indirect paths, Trust acts as a **Partial Mediator** across all three relationships. Thus, Hypothesis **{H4} is fully supported**.

4.6 Group differences (H5, H6)

- **Age Groups {H5}:** A one-way ANOVA across age groups yielded F(3, 246) = 4.82, p = .003, eta^2 = 0.055
- **Shopping Frequency {H6}):** An independent-samples t-test comparing frequent and occasional shoppers yielded t(248) = 3.64, p < .001, d = 0.47.

Analysis & Interpretation:

• {H5} (Age Differences): The ANOVA test supports {H5} by revealing significant differences in purchasing behavior across age groups (p =.003, eta^2 =.055). In comparison to older age groups (45+), younger cohorts (18–34) showed greater mean buying behavior ratings under AI control.

• {H6} (Shopping Frequency): Regular online customers show considerably more AI-influenced purchasing behavior (M = 3.84, SD = 0.62) than seldom shoppers (M = 3.51, SD = 0.70; t = 3.64, p <.001, d = 0.47), supporting {H6} with a modest effect size.

5. Discussion

Note. Once the findings are in, write this section. Below is a suggested structure. • List the hypotheses that were validated and contrast the three AI tools' effect sizes. • Connect results to earlier research. Tam and Ho (2006) and Komiak and Benbasat (2006) would concur with a positive personalizing impact; the personalization paradox would be echoed by a weak or negative one (Aguirre et al., 2015). • Compare chatbot results to those of Chung et al. (2020) and Xu et al. (2020), and compare DSS results to those of Logg et al. (2019) and Dietvorst et al. (2015). • Describe the findings of the mediation about trust as the mechanism.

5.1 Managerial implications

Retailers should build chatbots to delegate hard jobs to human employees, invest in the tool with the greatest standardized effect, and make data use public to allay privacy concerns.

5.2 Limitations and future research

Purposive sample restricts generalizability, and the cross-sectional, self-reported design restricts causal claims. Experiments, behavioral log data, cross-cultural sampling, and longitudinal designs could all be used in future research.

6. Conclusion

With trust serving as the explanatory link, this study provides an integrated examination of the relationship between consumer purchasing behavior and personalization, conversational AI, and decision support. It assists retailers in determining where AI investment is most likely to alter consumer behavior by looking at the three tools collectively.

References

[1] Aguirre, E., Mahr, D., Grewal, D., de Ruyter, K., & Wetzels, M. (2015). Unraveling the personalization paradox: The effect of information collection and trust-building strategies on online advertisement effectiveness. *Journal of Retailing, 91*(1), 34–49.

[2] Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes, 50*(2), 179–211.

[3] Ansari, A., & Mela, C. F. (2003). E-customization. *Journal of Marketing Research, 40*(2), 131–145.

[4] Bleier, A., Harmeling, C. M., & Palmatier, R. W. (2019). Creating effective online customer experiences. *Journal of Marketing, 83*(2), 98–119.

[5] Chung, M., Ko, E., Joung, H., & Kim, S. J. (2020). Chatbot e-service and customer satisfaction regarding luxury brands. *Journal of Business Research, 117*, 587–595.

[6] Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Lawrence Erlbaum Associates.

[7] 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.

[8] Davis, F. D. (1989).Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319–340.

[9] Dietvorst, B. J., Simmons, J. P., & Massey, C.(2015). Algorithm aversion: People erroneously avoid algorithms after seeing them err. *Journal of Experimental Psychology: General, 144*(1), 114–126.

[10] Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., … Williams, M. D. (2021). Artificial intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management, 57*, Article 101994.

[11] Field, A. (2018). *Discovering statistics using IBM SPSS Statistics* (5th ed.). Sage.

[12] Fornell, C., & Larcker, D. F.(1981). Evaluating structural equation models with un observable variables and measurement error. *Journal of Marketing Research, 18*(1), 39–50.

[13] Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in online shopping: An integrated model. *MIS Quarterly, 27*(1), 51–90.

[14] Grewal, D., Roggeveen, A. L., & Nordfält, J. (2017). The future of retailing. *Journal of Retailing, 93*(1), 1–6.

[15] Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate data analysis* (8th ed.). Cengage Learning.

[16] Hayes, A. F. (2018). *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach* (2nd ed.). Guilford Press.

[17] Hoyer, W. D., Kroschke, M., Schmitt, B., Kraume, K., & Shankar, V. (2020). Transforming the customer experience through new technologies. *Journal of Interactive Marketing, 51*, 57–71.

[18] Huang, M.-H., & Rust, R. T. (2018). Artificial intelligence in service. *Journal of Service Research, 21*(2), 155–172.

[19] Kaplan, A., & Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Business Horizons, 62*(1), 15–25.

[20] 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.

[21] Kumar, V., Rajan, B., Venkatesan, R., & Lecinski, J. (2019). Understanding the role of artificial intelligence in personalized engagement marketing. *California Management Review, 61*(4), 135–155.

[22] 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.

[23] Luo, X., Tong, S., Fang, Z., & Qu, Z. (2019). Frontiers: Machines vs. humans: The impact of artificial intelligence chatbot disclosure on customer purchases. *Marketing Science, 38*(6), 937–947.

[24] Nunnally, J. C., & Bernstein, I. H. (1994). *Psychometric theory* (3rd ed.). McGraw-Hill.

[25] Pavlou, P. A. (2003). Consumer acceptance of electronic commerce: Integrating trust and risk with the technology acceptance model. *International Journal of Electronic Commerce, 7*(3), 101–134.

[26] Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology, 88*(5), 879–903.

[27] 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.

[28] Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425–478.

[29] Xiao, B., & Benbasat, I. (2007). E-commerce product recommendation agents: Use, characteristics, and impact. *MIS Quarterly, 31*(1), 137–209.

[30] Xu, Y., Shieh, C.-H., van Esch, P., & Ling, I.-L. (2020). AI customer service: Task complexity, problem-solving ability, and usage intention. *Australasian Marketing Journal, 28*(4), 189–199.