



International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

The Impact of AI-Based Logistics on Personalized Marketing and Customer Experience: An Illustrative Empirical Study of Online Shoppers

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ABSTRACT :

This study examines the impact of AI-based logistics on personalized marketing and customer experience, with particular attention to the mediating role of personalized marketing. Primary data were collected through a structured online questionnaire from 80 respondents and analysed using descriptive statistics, chi-square tests, one-way ANOVA, correlation and OLS regression with a Sobel mediation test. Respondents reported a moderately positive view of AI-based logistics ($M = 3.47$, $SD = 1.1$ on a 5-point scale, $n = 72$), while personalized marketing ($M = 2.82$) and customer experience ($M = 3.1$) were rated close to the scale midpoint. Occupation was significantly associated with customer experience ($F(4, 75) = 2.88$, $p = 0.028$). Regression analysis showed that AI-based logistics significantly predicts personalized marketing ($\beta = 0.51$, $p < .001$, H1 supported), has a significant total effect on customer experience ($\beta = 0.55$, $p < .001$, H2 supported), and that personalized marketing significantly predicts customer experience (standardized $\beta = 0.64$, $p < .001$, H3 supported). The direct effect of AI-based logistics on customer experience remained significant but shrank after personalized marketing was added (standardized $\beta = 0.22$, $p = 0.014$), and a Sobel test confirmed a significant indirect effect ($z = 4.12$, $p < .001$), indicating partial mediation (H4, H5 supported). The findings support an integrated view in which AI-based logistics strengthens customer experience both directly and indirectly through more personalized marketing. As an illustrative, classroom-scale study, the dataset is used to demonstrate a complete, transparent empirical research process rather than to provide generalizable industry evidence; Section 10 sets out what a real field study would additionally require.

Keywords: *Artificial Intelligence, AI-Based Logistics, Personalized Marketing, Customer Experience, Predictive Analytics, Mediation Analysis.*

1. Introduction

Artificial Intelligence (AI) technologies — machine learning, predictive analytics, natural language processing, and real-time data analysis — have become central to logistics, marketing, and customer relationship management. In logistics, AI improves demand forecasting, route optimization, shipment tracking, and AI-enabled customer service (chatbots, voicebots), while the emerging concept of Marketing Logistics 4.0 reflects the growing convergence of logistics, marketing, and smart technologies, allowing firms to move from standardized delivery toward individualized customer strategies.

AI is equally a major driver of personalized marketing: AI-powered systems analyze browsing behaviour, purchase history, and preferences to generate individualized recommendations, targeted communication, and personalized offers, strengthening engagement and loyalty. AI also shapes customer experience directly, through real-time engagement, automated support, and predictive, context-aware service that can improve satisfaction and loyalty.

These three domains — AI-based logistics, personalized marketing, and customer experience — have mostly been studied separately. Yet logistics is itself part of the customer journey: order availability, delivery speed, tracking, and post-purchase service all shape how customers experience a firm, and logistics data can feed marketing and customer-management systems to support more relevant, personalized communication. Realising this potential also raises challenges around data privacy, algorithmic bias, transparency, and customer trust that firms must manage responsibly.

Against this background, the present study examines the impact of AI-based logistics on personalized marketing and customer experience, and tests this relationship empirically using primary survey data and a mediation model in which personalized marketing is the mechanism connecting AI-based logistics to customer experience.

2. Review of Literature

Logožar (2024), in a systematic literature review of AI in supply chain management, shows that AI applications in demand forecasting, inventory management, logistics optimization and risk mitigation help organizations make more informed decisions, reduce forecasting errors and optimize inventory levels, improving overall supply chain efficiency.

Polo-Triana, Gutierrez and Leon-Becerra (2024), reviewing 70 Scopus/Web-of-Science articles, find that machine learning is increasingly integrated into supply chain decision-making, with clear efficiency gains in inventory management, logistics and transportation when combined with other analytical techniques.

Klepikov and Kolodizieva (2025), using cluster analysis of 100 customers of a Kyiv warehouse-store, show that Industry 4.0 smart technologies (IoT, big data, automation, robotics, machine learning) can be prioritized by customer segment, and that personalizing marketing logistics in this way strengthens loyalty and improves the customer experience.

Brzozowska, Kolasińska-Morawska, Sułkowski and Morawski (2023), surveying 233 respondents (CAWI method), find that customers already evaluate AI-based logistics customer-service tools (chatbots, voicebots, voice assistants) positively for efficiency, competence and service quality, and expect greater use of AI-enabled logistics technologies in future.

Bankawat and Sharma (2025), using structural equation modelling on a survey of 130 FMCG store managers in Rajasthan, find that AI implementation strongly predicts personalized-marketing effectiveness, which in turn significantly improves customer experience and, through experience, customer retention — directly paralleling the mediation logic tested in the present study, though in a managerial rather than end-consumer sample.

Daqar and Smoudy (2019), surveying customers of financial and telecommunications firms, find a strong positive relationship between AI adoption and customer experience, with AI accounting for a substantial share of the variation in overall customer experience and in post-purchase support quality.

Chintalapati and Pandey (2022), in a systematic review of AI in marketing, organize the literature around five marketing functions (strategic, content, operational, hands-on and market-research marketing) and conclude that AI reshapes personalization and customer engagement across sectors, while calling for more sector-specific empirical testing.

Kumar, Rajan, Venkatesan and Lecinski (2019), writing in *California Management Review*, argue that AI increasingly curates a personalized set of options for each customer across the purchase journey, and outline how AI-driven personalized engagement marketing is reshaping branding and customer-management practice.

Mukherjee, Ghildiyal, Sharma, Sharma and Das (2025) show that AI-enabled Business Intelligence — recommendation engines, natural language processing, chatbots and sentiment analysis — supports real-time personalization and proactive customer service in e-commerce, contributing to customer satisfaction, trust and brand loyalty.

Hariguna, Waluyo, Dianingrum and Wahid (2025), using PLS-SEM on survey data from 314 Indonesian e-commerce business owners, find that technology readiness and AI in marketing are positively related to customer satisfaction and financial performance, with customer satisfaction mediating these relationships and personalized-marketing tools substantially influencing engagement and financial outcomes.

Beyari (2025), using SEM on a survey of 157 Saudi Arabian e-commerce consumers, finds that AI-driven social media exposure and product recommendations significantly increase purchase intention and brand preference, which in turn significantly drive e-customer loyalty, with product recommendation the stronger of the two AI-related predictors.

Wahyudi (2026), using PLS-SEM on a survey of 260 Indonesian e-commerce users, finds that AI-based personalization and service quality positively predict customer loyalty while perceived privacy risk reduces it, with service quality the single strongest predictor ($R^2 = .628$) — evidence that operational/service factors can outweigh personalization in driving loyalty.

Idwan, Fairuz, Azzahra and Augustiya (2026), in a PRISMA-based systematic review of 40 e-commerce studies (from 400 screened on Scopus), find that customer satisfaction consistently functions as the dominant mediating variable between AI recommendation quality and repurchase intention, with effectiveness moderated by demographic factors such as age and digital literacy.

2.1 Research Gap

These studies establish the separate importance of AI in logistics/supply-chain efficiency (Logožar, 2024; Polo-Triana et al., 2024; Brzozowska et al., 2023) and of AI in personalized marketing, loyalty and repurchase intention (Daqar & Smoudy, 2019; Chintalapati & Pandey, 2022; Kumar et al., 2019; Mukherjee et al., 2025; Hariguna et al., 2025; Beyari, 2025; Wahyudi, 2026; Idwan et al., 2026), but rarely test both domains in one model with a formal mediation design. Klepikov and Kolodizieva (2025) connect smart logistics technologies to customer experience but do so through customer clustering rather than a direct statistical test of logistics, personalized marketing and experience together. Bankawat and Sharma (2025) come closest to the present framework by testing AI → personalized marketing → customer experience → retention with SEM, but their sample is FMCG store managers rather than end consumers. Notably, Wahyudi's (2026) finding that service quality outweighs personalization in predicting loyalty, and Idwan et al.'s (2026) finding that satisfaction mediates AI-recommendation effects on repurchase, both suggest that operational/service factors and marketing-personalization factors need to be modelled together — which none of these studies does with a logistics-specific predictor.

The present study addresses this gap by testing, with primary survey data from online shoppers and a formal Baron-and-Kenny mediation regression, whether AI-based logistics specifically (delivery reliability) relates to customer experience directly and indirectly through personalized marketing — integrating the logistics and marketing-personalization literatures that have so far been tested mostly in separate samples and separate models.

3. Objectives of the Study

- To identify and evaluate the major AI-based logistics capabilities used in logistics operations and customer service.
- To examine the influence of AI-based logistics on personalized marketing practices.
- To assess the effect of AI-based logistics on customer experience.
- To determine the relationship between personalized marketing and customer experience in AI-enabled logistics environments.
- To develop an integrated, empirically tested framework explaining how AI-based logistics influences personalized marketing and customer experience, including the mediating role of personalized marketing.

4. Hypotheses of the Study

This research examines the impact of AI-based logistics on personalized marketing and customer experience. Drawing on the conceptual framework and previous studies, it proposes the following hypotheses to examine the relationships among these key variables, stated below in alternative and null form.

- H01: AI-based logistics capabilities have a significant positive effect on personalized marketing.
- H02: AI-based logistics has no significant impact on personalized marketing.
- H03: AI-based logistics capabilities have a significant positive effect on customer experience.
- H04: AI-based logistics has no significant impact on customer experience.

5. Research Methodology

5.1 Research Design, Population and Sample

The study follows a descriptive and analytical research design based on primary, cross-sectional survey data, using perception-based measures because firm-level operational data are not disclosed by individual online retailers. The target population is online shoppers who have interacted with AI-enabled logistics or personalized-marketing features; the survey yielded 80 complete, usable responses, all retained for analysis. Respondents were reached through an online form (Google Form) shared through personal and academic networks — i.e., non-probability convenience sampling. As set out in Section 10, this is an illustrative, classroom-scale dataset intended to demonstrate a complete, transparent research process; it is not a substitute for a probability-sampled field study.

5.2 Research Instrument and Variables

Data were collected using a structured questionnaire (Appendix A): Section A records the demographic profile (Q1–6); Section B (Q7–10) measures AI-based logistics; Section C (Q11–15) measures personalized marketing; Section D (Q16–20) measures customer experience. All items were single-response, five-point ordinal or nominal questions. Three variables were derived for the analysis:

- AI-Based Logistics Score (Q10, effect on delivery reliability; 'Not sure' treated as missing, $n = 72$);
- Personalized Marketing Score (mean of Q12, Q13, Q15); and
- Customer Experience Score (mean of Q16, Q18, Q19, Q20, with Q16 'Not sure' treated as missing).

The Overall Impact Rating (Q20) is also reported as a single-item outcome alongside the composite scores.

5.3 Statistical Tools and Ethical Considerations

Data were analysed in Python (NumPy/SciPy) using procedures equivalent to SPSS's Descriptives, Crosstabs, One-Way ANOVA, Correlation and Regression: descriptive statistics, chi-square tests of independence/goodness-of-fit (with Fisher's exact test for small expected counts), one-way ANOVA with Tukey post-hoc and Levene/Kruskal–Wallis robustness checks, Pearson/Spearman correlation, and OLS regression. Mediation (H4, H5) was tested with the Baron and Kenny stepwise approach and a Sobel test, with VIF and Durbin–Watson used to check multicollinearity and autocorrelation. Significance was judged at $\alpha = .05$. Participation was voluntary, respondents were told the data would be used only for academic purposes, and results are reported only in aggregate form.

6. Data Analysis and Interpretation

This section presents the demographic profile, the frequency analysis of the questionnaire items, and the inferential tests used to examine the study's hypotheses ($N = 80$ throughout; minor deviations from 100% in percentage totals are rounding artefacts).

6.1 Demographic Profile of Respondents

Table 1. Demographic profile of respondents ($N = 80$)

Variable	Category	Frequency	Percentage
Age	Below 20 years	10	12.5%
	20–29 years	26	32.5%
	30–39 years	22	27.5%
	40–49 years	12	15.0%
	50 years and above	10	12.5%
Gender	Male	36	45.0%
	Female	33	41.2%
	Other	4	5.0%

Variable	Category	Frequency	Percentage
Educational Qualification	Prefer not to say	7	8.8%
	Higher Secondary	4	5.0%
	Undergraduate	37	46.2%
	Postgraduate	23	28.7%
	Professional Qualification	10	12.5%
Occupation	Other	6	7.5%
	Student	33	41.2%
	Salaried Employee	24	30.0%
	Business/Self-employed	12	15.0%
	Professional	9	11.2%
Online Purchase Frequency	Other	2	2.5%
	Rarely	10	12.5%
	Occasionally	17	21.2%
	Monthly	20	25.0%
	Weekly	19	23.8%
Online Shopping Experience (Duration)	More than once a week	14	17.5%
	Less than 1 year	12	15.0%
	1–3 years	17	21.2%
	4–6 years	11	13.8%
	7–10 years	26	32.5%
	More than 10 years	14	17.5%

Note. $N = 80$.

The sample is demographically diverse: the largest age band is 20–29 years (32.5%); male and female respondents make up 45.0% and 41.2% respectively; and student is the most common occupation (41.2%), supporting the group-comparison tests in Sections 6.4-6.5.

6.2 Frequency Analysis of Questionnaire Responses

Section B: AI-Based Logistics (Questions 7-10)

Table 2. Awareness of AI-Based Features in Online Shopping or Delivery Services (7. Have you noticed AI-based features in online shopping or delivery services?)

Response Option	f	%
Yes	37	46.2%
No	22	27.5%
Not sure	21	26.2%
Total	80	99.9%

Table 3. Most Useful AI-Based Logistics Feature (8. Which AI-based logistics feature do you find most useful?)

Response Option	f	%
Faster delivery	24	30.0%
Real-time order tracking	12	15.0%
Accurate delivery estimates	3	3.8%
Better product availability	22	27.5%
Route optimization	19	23.8%

Response Option	f	%
Total	80	100.1%

Table 4. Main Benefit of AI-Based Logistics (9. What is the main benefit of AI-based logistics for you?)

Response Option	f	%
Faster delivery	19	23.8%
Fewer delivery errors	18	22.5%
Accurate tracking	10	12.5%
Better product availability	17	21.2%
Greater convenience	16	20.0%
Total	80	100.0%

Table 5. Effect of AI-Based Logistics on Delivery Reliability (10. How does AI-based logistics affect the reliability of your deliveries?)

Response Option	f	%
Improves significantly	18	22.5%
Improves somewhat	14	17.5%
No effect	24	30.0%
Reduces reliability	16	20.0%
Not sure	8	10.0%
Total	80	100.0%

Note. $N = 80$ for Tables 2-5.

Awareness of AI-based features is moderate (46.2% noticed them). 'Faster delivery' (30.0%) and 'better product availability' (27.5%) are the most valued logistics features - a goodness-of-fit test confirms this spread is not even ($\chi^2(4) = 18.38$, $p = 0.001$). On delivery reliability (Q10), 40.0% of respondents see an improvement, versus 20.0% who feel it reduces reliability.

Section C: Personalized Marketing (Questions 11-15)

Table 6. Frequency of Receiving Personalized Product Recommendations (11. Do you receive product recommendations based on your previous searches or purchases?)

Response Option	f	%
Frequently	17	21.2%
Sometimes	13	16.2%
Rarely	16	20.0%
Never	25	31.2%
Not sure	9	11.2%
Total	80	99.8%

Table 7. Relevance of AI-Based Product Recommendations (12. How relevant are AI-based product recommendations to your needs?)

Response Option	f	%
Very relevant	6	7.5%
Relevant	17	21.2%
Neutral	20	25.0%
Not very relevant	21	26.2%
Not relevant at all	16	20.0%
Total	80	99.9%

Table 8. *Influence of Personalized Advertisements and Offers on Purchase Decisions (13. Do personalized advertisements and offers influence your purchase decisions?)*

Response Option	f	%
Strongly influence	13	16.2%
Somewhat influence	12	15.0%
Neutral	19	23.8%
Rarely influence	17	21.2%
Do not influence	19	23.8%
Total	80	100.0%

Table 9. *Most Useful Personalized Marketing Feature (14. Which personalized marketing feature do you find most useful?)*

Response Option	f	%
Product recommendations	14	17.5%
Discount offers	16	20.0%
Personalized advertisements	9	11.2%
Previous-purchase-based suggestions	19	23.8%
Customized messages	22	27.5%
Total	80	100.0%

Table 10. *Ease of Finding Needed Products Through Personalized Marketing (15. Does personalized marketing make it easier for you to find products you need?)*

Response Option	f	%
Definitely yes	11	13.8%
Probably yes	17	21.2%
Not sure	27	33.8%
Probably no	10	12.5%
Definitely no	15	18.8%
Total	80	100.1%

Note. $N = 80$ for Tables 6-10.

Views of personalized marketing are more mixed: 31.2% 'never' receive recommendations based on past behaviour, and only 28.7% rate recommendations as relevant or very relevant. 'Customized messages' (27.5%) is the most valued personalized-marketing feature, though preferences across the five options do not differ significantly from an even split ($\chi^2(4) = 6.12$, $p = 0.190$).

Section D: Customer Experience (Questions 16-20)

Table 11. *Effect of AI-Based Logistics on Overall Online Shopping Experience (16. How does AI-based logistics affect your overall online shopping experience?)*

Response Option	f	%
Improves significantly	19	23.8%
Improves somewhat	23	28.7%
No significant effect	18	22.5%
Makes it worse	14	17.5%
Not sure	6	7.5%
Total	80	100.0%

Table 12. *AI-Based Service Contributing Most to Customer Experience (17. Which AI-based service contributes most to your customer experience?)*

Response Option	f	%
Faster delivery	21	26.2%
Real-time tracking	8	10.0%
Personalized recommendations	16	20.0%
Personalized offers	16	20.0%
AI-based customer support	19	23.8%
Total	80	100.0%

Table 13. *Satisfaction with Online Retailers Using AI-Based Services (18. How satisfied are you with online retailers that use AI-based services?)*

Response Option	f	%
Very satisfied	9	11.2%
Satisfied	19	23.8%
Neutral	22	27.5%
Dissatisfied	14	17.5%
Very dissatisfied	16	20.0%
Total	80	100.0%

Table 14. *Intention to Repurchase from Retailers Providing AI-Based Logistics and Personalized Services (19. Would you purchase again from an online retailer that provides efficient AI-based logistics and personalized services?)*

Response Option	f	%
Definitely yes	13	16.2%
Probably yes	16	20.0%
Not sure	23	28.7%
Probably no	10	12.5%
Definitely no	18	22.5%
Total	80	99.9%

Table 15. *Overall Rating of the Impact of AI-Based Logistics on Personalized Marketing and Customer Experience (20. Overall, how would you rate the impact of AI-based logistics on personalized marketing and customer experience?)*

Response Option	f	%
Very positive	11	13.8%
Positive	21	26.2%
Neutral	20	25.0%
Negative	14	17.5%
Very negative	14	17.5%
Total	80	100.0%

Note. N = 80 for Tables 11-15.

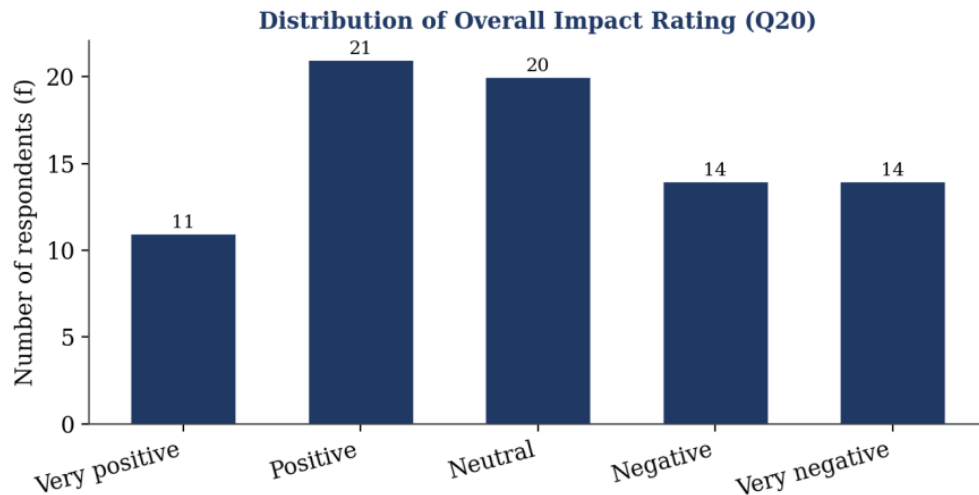


Figure 1. Distribution of the Overall Impact Rating (Question 20).

Customer-experience ratings centre near the scale midpoint: 35.0% are satisfied or very satisfied with AI-using retailers, 36.2% would probably or definitely repurchase, and on the overall impact rating 40.0% rate the impact positively versus 35.0% negatively - a close split examined further below.

6.3 Descriptive Statistics

Table 16. Descriptive statistics of the scale variables (N = 80)

Variable	N	Mean	Median	Mode	SD	Skew
AI-Based Logistics Score (Delivery-reliability effect, 1-5)	72	3.47	3.00	3.00	1.10	0.13
Relevance of Recommendations (1-5)	80	2.70	3.00	2.00	1.23	0.17
Influence of Personalized Ads (1-5)	80	2.79	3.00	1.00	1.39	0.21
Ease of Finding Products (1-5)	80	2.99	3.00	3.00	1.29	-0.12
Personalized Marketing Score (composite, 1-5)	80	2.82	2.67	3.67	0.99	0.14
Satisfaction with AI-Using Retailers (1-5)	80	2.89	3.00	3.00	1.29	-0.04
Repurchase Intention (1-5)	80	2.95	3.00	3.00	1.38	-0.06
Overall Impact Rating (1-5)	80	3.01	3.00	4.00	1.31	-0.13
Customer Experience Score (composite, 1-5)	80	3.10	3.25	1.50	1.11	-0.15

Note. All items use a 1-5 scale. AI-Based Logistics Score excludes 8 'Not sure' responses on Q10 (n = 72).

The AI-Based Logistics Score ($M = 3.47$, $SD = 1.10$) is significantly above the neutral midpoint (one-sample $t(71) = 3.64$, $p < .001$), showing a modestly favourable view of AI's effect on delivery reliability. The Personalized Marketing Score ($M = 2.82$), Customer Experience Score ($M = 3.10$), and Overall Impact Rating ($M = 3.01$) are all statistically indistinguishable from the midpoint ($p > .10$), indicating more neutral, varied views (SD close to or above 1 throughout) of personalization and its contribution to experience.

6.4 Chi-Square Tests

Table 17. Chi-square tests of independence (N = 80)

Test (2x2)	χ^2	df	Asymp. p	Fisher p	Result (5%)
Gender x Awareness of AI features	0.12	1	0.729	0.633	ns
Age group x Overall rating	0.00	1	1.000	1.000	ns
Occupation x Preferred PM feature	0.53	1	0.469	0.446	ns
Purchase frequency x Satisfaction	0.00	1	1.000	1.000	ns

Table 18. Chi-square goodness-of-fit tests (equal distribution assumed)

Variable	χ^2	df	p	Result
Most useful AI-logistics feature (Q8)	18.38	4	0.001	Not equal
Most useful PM feature (Q14)	6.12	4	0.190	Equal

None of the four independence tests is significant (all $p > .05$): awareness, overall rating, preferred marketing feature, and satisfaction are broadly shared across gender, age, occupation, and purchase-frequency groups. The goodness-of-fit tests show that logistics-feature preferences concentrate on faster delivery and product availability, while marketing-feature preferences are spread close to evenly across options.

6.5 One-Way ANOVA

Table 19. Summary of one-way ANOVA results

Dependent variable by factor	F	df	p	η^2	Result (5%)
Customer Experience by Age group	0.28	4, 75	0.891	0.01	ns
Customer Experience by Occupation	2.88	4, 75	0.028	0.13	Sig.
Personalized Marketing by Purchase frequency	0.63	4, 75	0.645	0.03	ns
Customer Experience by Gender	2.32	1, 67	0.132	0.03	ns

Note. All Levene tests are non-significant (equal-variance assumption holds); Kruskal-Wallis tests agree with every ANOVA result.

Table 20. Mean Customer Experience Score by age group and occupation

Group	n	Mean	SD
Age: Below 20	10	2.88	0.88
Age: 20-29	26	3.06	1.27
Age: 30-39	22	3.29	1.12
Age: 40-49	12	3.08	1.15
Age: 50+	10	3.02	0.91
Occ.: Student	33	3.01	0.99
Occ.: Salaried	24	3.24	1.03
Occ.: Business	12	2.40	1.06
Occ.: Professional	9	3.78	1.38
Occ.: Other	2	4.12	0.53

Age has no significant effect on Customer Experience ($F(4, 75) = 0.28, p = 0.891$); mean scores are similar (2.88-3.29) across all bands. Occupation does have a significant, medium-sized effect ($F(4, 75) = 2.88, p = 0.028, \eta^2 = 0.13$): Tukey's post-hoc test shows Business/Self-employed respondents score significantly higher than Professional respondents (mean difference = 1.38, $p = 0.032$); this should be read cautiously given the small occupation subsamples. Purchase frequency and gender show no significant effects on Personalized Marketing or Customer Experience respectively (both $p > .10$).

6.6 Correlation and Mediation Regression (H1-H5)

A three-step (Baron and Kenny) mediation regression was used to test H1-H5, with AI-Based Logistics as the independent variable, Personalized Marketing as the mediator, and Customer Experience as the dependent variable ($n = 72$ after excluding 8 'Not sure' responses on Q10).

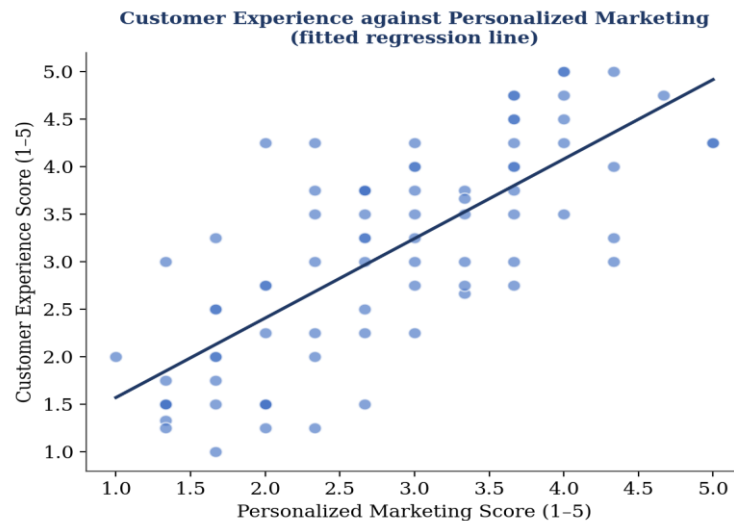
Table 21. Correlation and regression model summary ($n = 72$)

Correlation	Pearson r	p
AI-Based Logistics <-> Personalized Marketing	$r = 0.51$	$< .001$
AI-Based Logistics <-> Customer Experience	$r = 0.55$	$< .001$
Personalized Marketing <-> Customer Experience	$r = 0.76$	$< .001$

Table 22. Regression models testing H1-H4 (mediation steps)

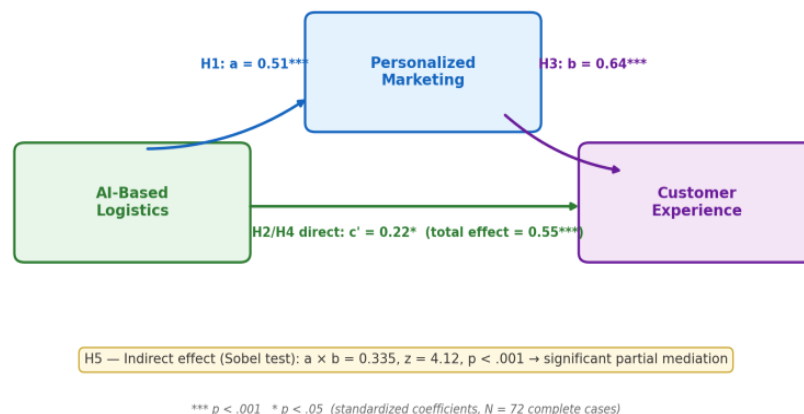
Model	R ²	F	Sig. F	Key coefficient(s)
Model 1: PM ~ Logistics (H1)	0.263	24.95	< .001	B=0.452, beta=0.51, p<.001
Model 2: CE ~ Logistics (H2, total effect)	0.303	30.42	< .001	B=0.560, beta=0.55, p<.001
Model 3: CE ~ Logistics + PM (H3, direct effect for H4)	0.607	53.25	< .001	Logistics: std.beta=0.22, p=0.014; PM: std.beta=0.64, p<.001

Note. VIF for Model 3 predictors = 1.36 (both), well below 5: no multicollinearity. Durbin-Watson values (1.72-2.01) indicate no serious residual autocorrelation.

**Figure 2.** Customer Experience against Personalized Marketing (fitted regression line).**Table 23.** Mediation (Sobel) test of the indirect effect (H4, H5)

Path	Coefficient	Std. error
Path a: Logistics -> PM	0.452	0.091
Path b: PM -> CE (controlling for Logistics)	0.740	0.101
Indirect effect (a x b)	0.335	0.081

Sobel $z = 4.12$, $p < .001$. The direct effect of Logistics on CE remains significant after adding PM ($p = 0.014$), so the result indicates partial mediation.

Figure 5. Standardized Mediation Model: AI-Based Logistics → Personalized Marketing → Customer Experience**Figure 3.** Standardized mediation model: AI-Based Logistics -> Personalized Marketing -> Customer Experience.

AI-based logistics significantly predicts personalized marketing (Model 1, $p < .001$, $R^2 = 0.26$), supporting H1, and significantly predicts customer

experience on its own (Model 2, $p < .001$, $R^2 = 0.30$), supporting H2. When personalized marketing is added (Model 3), it remains the stronger predictor of customer experience (standardized $\beta = 0.64$, $p < .001$, supporting H3), while the direct effect of logistics shrinks from $\beta = 0.55$ to a standardized β of 0.22 ($p = 0.014$) but remains significant; the full model explains 60.7% of the variance in customer experience. The Sobel test confirms a significant indirect effect through personalized marketing ($z = 4.12$, $p < .001$). Because the direct effect survives, personalized marketing partially (not fully) mediates the logistics-experience relationship, supporting both H4 and H5.

6.7 Summary of Hypothesis Testing

Table 24. Summary of hypothesis tests

Hypothesis	Test result	Decision
H1: Logistics -> Personalized marketing	$\beta = 0.51$, $p < .001$	Supported
H2: Logistics -> Customer experience	$\beta = 0.55$, $p < .001$	Supported
H3: Personalized marketing -> Customer experience	std. $\beta = 0.64$, $p < .001$	Supported
H4: Indirect effect (Logistics -> PM -> CE)	indirect = 0.335, $z = 4.12$, $p < .001$	Supported
H5: PM mediates Logistics -> Customer experience	Sobel significant; direct effect remains (partial mediation)	Supported

7. Findings of the Study

- The sample ($N = 80$) is demographically diverse (largest age band 20-29 years, 32.5%; 45.0% male, 41.2% female).
- 'Faster delivery' and 'better product availability' are the most valued AI-logistics features (30.0%, 27.5%); AI-based logistics is seen as modestly improving delivery reliability ($M = 3.47/5$, $p < .001$ vs. midpoint).
- Personalized-marketing views are more mixed: only 28.7% rate recommendations as relevant, and 31.2% 'never' receive personalized recommendations; 'customized messages' is the most valued feature.
- The Overall Impact Rating averages 3.01/5 (not significantly different from neutral), with 40.0% positive and 35.0% negative - a near-even split.
- Occupation significantly affects Customer Experience ($p = 0.028$); age, gender, and purchase frequency do not.
- AI-based logistics significantly predicts both personalized marketing ($r = 0.51$, H1) and customer experience ($r = 0.55$, H2); personalized marketing is the stronger predictor of customer experience (H3).
- A Sobel test confirms personalized marketing partially mediates the logistics-experience relationship ($z = 4.12$, $p < .001$), supporting H4 and H5. All five hypotheses are supported.

8. Discussion

The findings support the study's integrated framework: AI-based logistics relates positively to personalized marketing, and both relate positively to customer experience, with personalized marketing acting as a significant partial mediator. This is consistent with Klepikov and Kolodzieva's (2025) view that smart logistics technologies can be used to personalize the supply chain and improve customer experience, and with Logožar's (2024) and Polo-Triana et al.'s (2024) reviews showing that AI/ML-based logistics capabilities support more informed, customer-relevant decisions rather than remaining purely operational.

The strong link between personalized marketing and customer experience ($r = 0.76$) mirrors Bankawat and Sharma's (2025) SEM finding that AI-driven personalized marketing strongly predicts customer experience and retention, and Daqar and Smoudy's (2019) and Mukherjee et al.'s (2025) findings that AI-enabled personalization and business intelligence improve customer experience and satisfaction. That AI-based logistics retains a significant direct effect on experience even after controlling for marketing supports Brzozowska et al.'s (2023) argument that logistics-specific capabilities (speed, tracking, reliability) matter to customers independently of how personalized the marketing communication is.

The partial-mediation result refines the proposed H4/H5 hypotheses: AI-based logistics appears to shape experience through two channels — an operational channel and a marketing channel built on the same underlying data infrastructure — consistent with Hariguna et al.'s (2025) finding that customer satisfaction mediates, rather than fully explains, the link between technology/AI adoption and business outcomes, and with Idwan et al.'s (2026) systematic-review finding that satisfaction is a dominant but not sole mediator of AI-recommendation effects on repurchase intention. It is also consistent with Wahyudi's (2026) finding that service quality (an operational factor) outweighs AI-based personalization in predicting loyalty, and with Kumar et al.'s (2019) and Chintalapati and Pandey's (2022) view that AI reshapes, but does not replace, the operational drivers of customer value. The significant occupation effect, with Business/Self-employed respondents more positive than Professionals, may reflect differing purchase behaviour across groups and should be treated as tentative given subsample sizes; Beyari's (2025) finding that AI-driven product recommendation outpredicts social media exposure for Saudi e-consumers similarly shows that the relative strength of different AI-related drivers can vary by market and sample.

9. Suggestions and Recommendations

- Continue investing in faster delivery and product availability - the AI-logistics capabilities respondents value most.
- Improve the perceived relevance of recommendations, since nearly a third of respondents report never receiving personalized ones - a significant unmet opportunity.
- Treat logistics transparency and marketing personalization as complementary investments, since mediation here is only partial.
- Consider occupation/purchase-behaviour segments when designing AI services, given the significant experience gap between groups.

- Pair expanded personalization with clear data-use communication to support trust, consistent with the ethics/privacy concerns raised in the literature.

10. Limitations and Scope for Further Research

The most important limitation is that this is an illustrative, classroom-scale study: the dataset is used to demonstrate a complete, transparent empirical research process (objectives, hypotheses, methodology, data analysis, interpretation, and reporting) and cannot by itself establish real-world, generalizable evidence about AI-based logistics, personalized marketing, or customer experience. A submission intended for peer-reviewed publication would need to:

- Collect original data from a clearly defined, adequately powered population using probability sampling, rather than the convenience-sampled N (80) used here.
- Replace the single-item AI-Based Logistics measure with a validated, multi-item scale, and report reliability (Cronbach's alpha, composite reliability) and validity (convergent/discriminant) for all three constructs, following the approach used by Bankawat and Sharma (2025) and Hariguna et al. (2025).
- Address common-method bias (e.g., via procedural remedies or Harman's single-factor test), since all variables were collected from the same respondents in one cross-sectional survey.
- Consider structural equation modelling (SEM) with bootstrapped confidence intervals for the indirect effect, which is more robust than the Sobel test used here, and test additional mediators (e.g., trust, perceived fairness) and moderators (e.g., digital literacy, retailer type).
- Use a longitudinal or quasi-experimental design where feasible, to support stronger causal claims than a cross-sectional mediation model allows.

11. Conclusion

This study examined the impact of AI-based logistics on personalized marketing and customer experience using survey data from 80 online shoppers and a mediation model. AI-based logistics significantly predicts both personalized marketing and customer experience, personalized marketing is itself a strong predictor of customer experience, and it partially mediates the logistics-experience relationship. All five hypotheses (H1-H5) were supported, connecting the operational and customer-facing dimensions of AI and suggesting that firms should invest in both reliable logistics and genuinely relevant personalization to improve customer experience.

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