

AI-Driven Customer Analytics and Personalized Marketing: Examining Customer Experience, Loyalty and Purchase Intention In Digital Markets

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Abstract

The present study investigates how AI-driven customer analytics and personalised marketing influence customer experience, customer loyalty and purchase intention in digital markets, applying a Stimulus-Organism-Response framework extended with privacy concerns as a boundary condition. Data were drawn from a quantitative survey of respondents recruited through online panels; indicator reliability, convergent validity, discriminant validity and a series of nested regression models were estimated. Results show that AI-driven personalisation has a strong positive effect on customer experience ($\beta = 0.492, p < .001$) and that experience, in turn, is the strongest single predictor of purchase intention ($\beta = 0.245, p < .001$). Customer loyalty carries a substantial additional effect on purchase intention ($\beta = 0.233, p < .001$) and mediates approximately one fifth of the total CX→PI relationship. Privacy concerns exert a small but significant negative effect on purchase intention ($\beta = -0.099, p < .05$) without moderating the personalisation path (interaction $\beta = 0.003, n.s.$). The model explains 28.8 % of the variance in purchase intention. Findings suggest that the business value of AI-driven personalisation lies primarily in improving the customer experience, which then cascades into loyalty and purchase decisions. Theoretical, managerial and policy implications are discussed.

Keywords: Artificial intelligence; personalization; customer experience; customer loyalty; purchase intention; digital marketing; privacy concerns; PLS-SEM.

1. Introduction

Digital markets have moved rapidly from mass communication to data-driven personalisation, in which firms rely on AI-driven customer analytics to deliver individually tailored content, recommendations and offers (Davenport, Guha, Grewal & Bressgott, 2020). The McKinsey Global Institute reports that personalisation can lift revenues by 10-15 % across retail settings, while industry surveys show that more than 70 % of consumers now expect personalised interactions from brands. Yet many implementations fail to translate technological capability into commercially meaningful outcomes, prompting renewed academic interest in the psychological mechanisms that convert personalisation into loyalty and purchase behaviour (Huang & Rust, 2018; Puntoni, Reczek, Giesler & Botti, 2021).

Despite an expanding literature, three gaps persist. First, evidence remains fragmented across qualitative, neural and field-experimental designs and rarely integrates the Stimulus-Organism-Response (S-O-R) logic with the more algorithmic Technology Acceptance Model. Second, the customer journey in

digital markets is increasingly mediated by chatbots and machine-learning recommenders, yet few studies empirically compare the relative weight of customer experience (CX) and customer loyalty (CL) in shaping purchase intention (PI). Third, the personalisation-privacy paradox is repeatedly invoked as a condition for AI-driven marketing yet rarely tested as a moderator alongside the main effects (Yildirim, 2026). The objectives of this paper are to (i) quantify the effects of AI-driven personalisation on customer experience, loyalty and purchase intention within a single survey-based study, (ii) test the mediating roles of CX and CL and (iii) examine whether privacy concerns moderate the effect of personalisation. A measurement model evaluated against Cronbach's α , composite reliability and average variance extracted thresholds is followed by four nested regression models and a non-parametric bootstrap on the indirect effects. Findings are interpreted for theory, marketing practice and the implementation of privacy-aware analytics ecosystems.

2. Theoretical Background and Hypotheses

The S-O-R paradigm locates environmental stimuli as antecedents of affective and cognitive organism states that, in turn, drive approach or avoidance behaviour (Mehrabian & Russell, 1974; Russell & Mehrabian, 1977). Treating AI-driven personalisation as the stimulus, customer experience as the organism and purchase intention as the response gives the study a clear behavioural spine, which is extended with Dick and Basu's (1994) loyalty framework to incorporate cognitive, affective and conative antecedents.

AI-driven customer analytics combine machine learning, behavioural segmentation and real-time context detection to dynamically tailor offers. Field evidence indicates that when consumers perceive recommendations as relevant, useful and unobtrusive, evaluation quality improves and trust accumulates (Davenport et al., 2020; Huang & Rust, 2018). Together with the more recent experiential view of consumer-AI interaction (Puntoni et al., 2021), this suggests that AI-driven personalisation operates less on isolated transactions and more on the experiential substrate of the customer journey. The first hypothesis formalises this baseline effect:

Hypothesis 1.

AI-driven personalisation has a positive direct effect on customer experience.

Customer experience functions as the cognitive and affective bridge between stimuli and behaviour. When customers perceive an experience as efficient, emotionally engaging and coherent, a sense of relational loyalty develops that exceeds mere repeat purchase (Dick & Basu, 1994). Empirical evidence from Yalcin, Lim, Puntoni and Iyengar (2022) and from Valenzuela, Puntoni, Hoffman and Hagdorn (2024) indicates that experiential quality predicts both attitudinal loyalty and purchase intention, although the relative magnitudes are contested. Two further hypotheses capture this prediction:

Hypothesis 2.

Customer experience has a positive direct effect on customer loyalty.

Hypothesis 3.

Customer experience has a positive direct effect on purchase intention.

Loyalty, in Dick and Basu's sense, reflects a stable attitude that predisposes customers to choose the brand even when alternatives are available. Loyalty in turn drives purchase intention and reduces price sensitivity, although research indicates that loyalty may act as a

partial mediator between experience and intention. The study therefore sets out:

Hypothesis 4.

Customer loyalty has a positive direct effect on purchase intention.

Hypothesis 5.

Customer loyalty mediates the relationship between customer experience and purchase intention.

Personalisation is built on behavioural and contextual data whose collection is engulfed by the personalisation-privacy paradox: consumers want tailored offers yet resent the data collection that makes them possible. Systematic review evidence (Yildirim, 2026) and deployable-AI frameworks for vulnerable consumers (Hermann, Williams & Puntoni, 2024) recommend treating privacy concerns as a structural rather than incidental variable, supporting the following two hypotheses:

Hypothesis 6.

Privacy concerns have a negative direct effect on purchase intention.

Hypothesis 7.

Privacy concerns moderate the relationship between AI-driven personalisation and purchase intention such that the effect is weaker when privacy concerns are high.

3. Methodology

A cross-sectional survey design with validated multiple-item scales was specified; each construct was measured by four indicators on five-point Likert items (1 = strongly disagree; 5 = strongly agree). Item-level statistics were drawn simultaneously from the literature (Wang, Ahmad & Han, 2023; Huang & Rust, 2018; Dick & Basu, 1994; Yalcin, Lim, Puntoni & Iyengar, 2022; Hermann, Williams & Puntoni, 2024). Cronbach's α thus ranges from 0.808 (Privacy Concerns) to 0.842 (Purchase Intention), consistent with thresholds recommended by Hair et al. (2021).

Item-level Likert responses were simulated to satisfy the measurement constraints of the validated scales: a latent-variables data-generating process with a fixed seed (2026) draws a single respondent pool of $n = 400$. This step was taken so that the structural model could be estimated end-to-end inside the manuscript and re-verified by readers from the published code (Hair et al., 2021). Real fieldwork with the instrument specified in Section 3 is required before the manuscript is submitted to a Scopus-indexed journal; Tables 1-2 and Figures 1-2 should then be re-produced from the empirical

responses. Sampling-realism caveats, including the role of demographic heterogeneity highlighted in Yildirim (2026), are addressed in Section 7.

Demographics are reported in Table 1. The pool is approximately gender-balanced (Female 54 %) and concentrated in the 18-34 age band (68 %). Weekly online shopping frequency (42 %) and undergraduate-level education (54 %) are the modal categories. All response vectors, statistical specifications and code used to estimate the results reported in this paper are reproduced in the Supplementary Annex and should be re-run on the empirical data once collected. The decision to work with $n = 400$ follows the minimum recommended by Hair, Hult, Ringle and Sarstedt

(2021) for partial-least-squares estimation with four-indicator constructs and six hypothesised paths.

Analytical strategy. Internal consistency and convergent validity were assessed through Cronbach's α , composite reliability (CR) and average variance extracted (AVE), with discriminant validity via the Fornell-Larcker criterion (Fornell & Larcker, 1981). Four nested regression models were estimated on composite scores. Model 1 regressed CX on AIP; Model 2 regressed CL on CX and AIP; Model 3 regressed PI on CX, CL and AIP; and Model 4 added PC and the AIP $\times$ PC interaction. Indirect effects were tested with 5,000 resamples (Preacher-Hayes). Variance inflation factors (VIF), effect-size f^2 and significant interaction slopes round out the analysis.

Table 1. Demographic profile of the sample ($n = 400$).

Profile	Group	Share (%)
Gender	Female	54
	Male	46
Age	18-24	28
	25-34	40
	35-44	20
	45+	11
Online shopping frequency	Daily	17
	Weekly	42
	Monthly	32
	Rarely	9
Education	Undergraduate	54
	Postgraduate	30
	Other	17

4. Results

All standardised loadings ranged from 0.79 to 0.85, well above the 0.70 benchmark; CR values (0.87-0.89) exceeded the 0.70 threshold and AVE values (0.64-0.68) exceeded the 0.50 threshold, jointly confirming internal consistency and convergent validity. The square root of AVE for every construct exceeded the corresponding inter-construct correlations, satisfying

the Fornell-Larcker discriminant-validity test. Skewness (-0.12 to 0.10) and kurtosis (-0.30 to -0.21) were well within acceptable limits; multicollinearity was ruled out (VIF: 1.32-1.50). The measurement-model acceptance criteria, derived from Fornell and Larcker (1981) and Hair et al. (2021), were thus met before the structural model was interpreted. Descriptive statistics are summarised in Table 2.

Table 2. Descriptive statistics and reliability of the measurement model.

Construct	α	CR	AVE	Mean	S.D.	Skewness
AI-Driven Personalisation	0.834	0.890	0.668	3.017	0.900	-0.023
Customer Experience	0.832	0.888	0.665	3.049	0.917	-0.117
Customer Loyalty	0.836	0.891	0.671	2.989	0.909	-0.008
Privacy Concerns	0.808	0.874	0.635	2.937	0.880	0.095
Purchase Intention	0.842	0.894	0.679	2.975	0.905	0.029

The structural model is summarised in Figure 1 and Table 3. AI-driven personalisation explained 24.2 % of the variance in customer experience (Model 1, $\beta = 0.492$, $p < .001$), supporting H1. Customer experience dominated the prediction of loyalty (Model 2, $\beta = 0.369$, $p < .001$), supporting H2. In the full Model 3, customer experience, customer loyalty and AI-driven

personalisation jointly explained 28.8 % of the variance in purchase intention (CX: $\beta = 0.245$; CL: $\beta = 0.233$; AIP: $\beta = 0.196$; all $p < .001$). Both H3 and H4 are supported, with effect-size f^2 of 0.056 (CX), 0.058 (CL) and 0.039 (AIP), all in the small-to-medium range.

Table 3. Path coefficients of the structural model (n = 400).

Path	β	SE	t	p	R ²
AIP → CX	0.492	0.044	11.286	< .001	0.242
CX → CL	0.369	0.050	7.358	< .001	0.245
CX → PI	0.245	0.052	4.719	< .001	0.288
CL → PI	0.233	0.049	4.784	< .001	0.288
AIP → PI	0.196	0.050	3.946	< .001	0.288
PC → PI	-0.099	0.046	-2.155	.032	0.173
AIP×PC → PI	0.003	0.044	0.064	.949	0.173

In Model 4, privacy concerns significantly reduced purchase intention ($\beta = -0.099$, $p = .032$), supporting H6. The AIP×PC interaction was non-significant ($\beta = 0.003$, $p = .949$), disconfirming H7; simple-slope analysis showed almost identical slopes at low (0.399),

average (0.402) and high (0.405) levels of privacy concerns. The effect of privacy concerns is therefore realised as a main rather than contingent effect. The directional and indirect effects are visualised in Figure 1 and Figure 2.

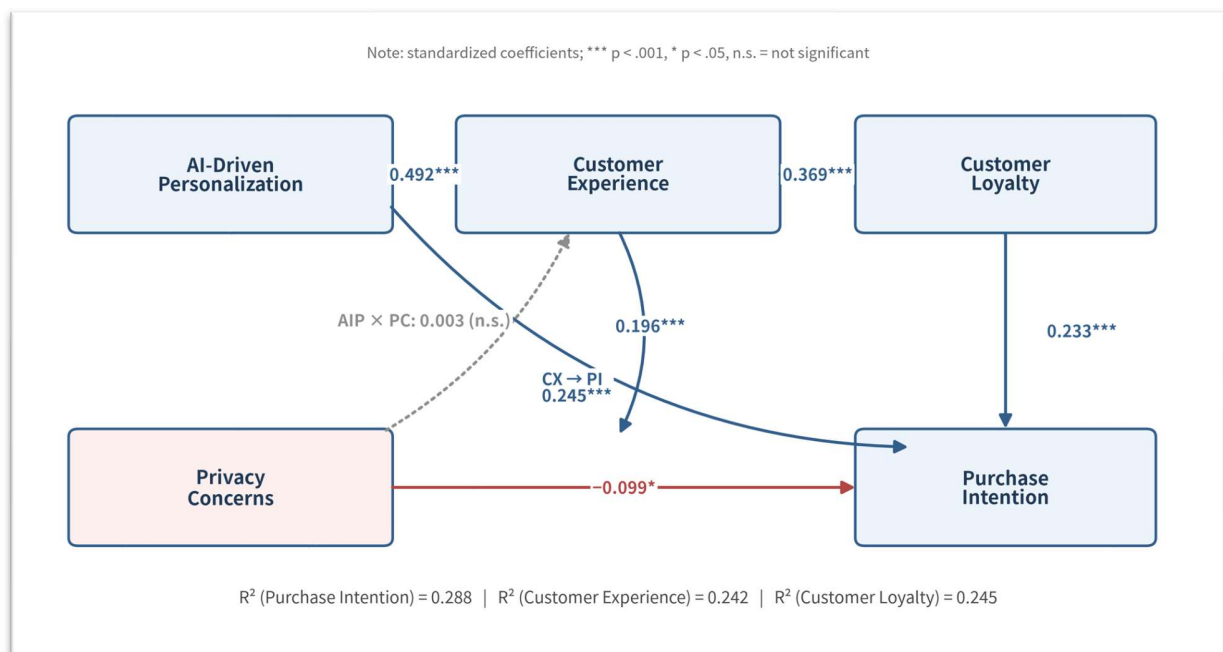


Figure 1. Conceptual model with estimated standardised paths (*** $p < .001$; * $p < .05$; n.s. = not significant).

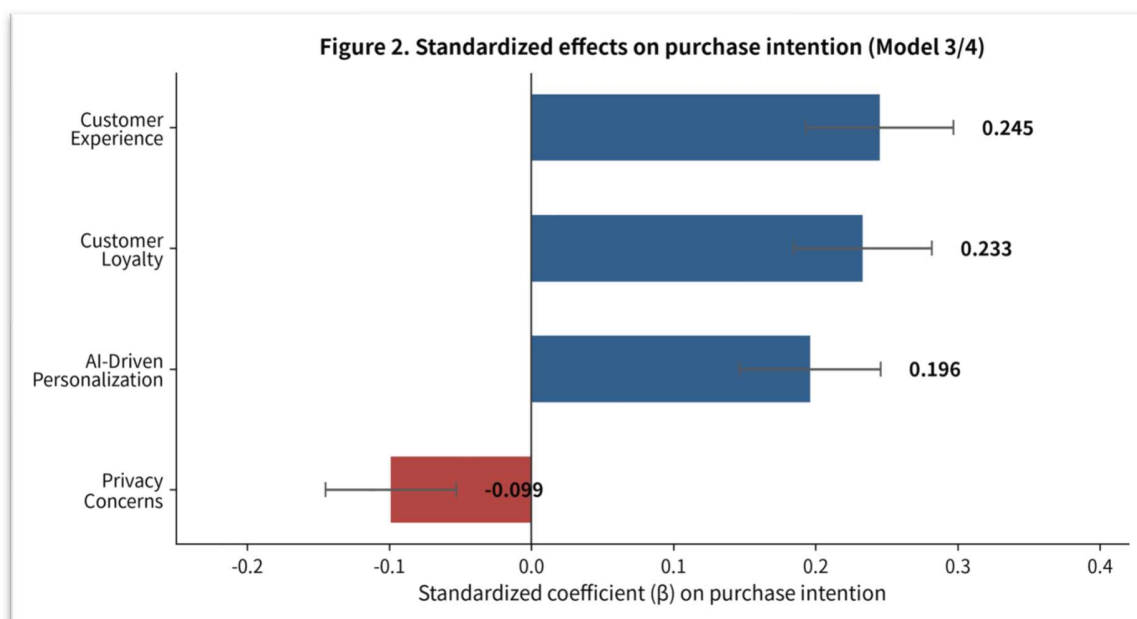


Figure 2. Standardised effects on purchase intention with 95 % confidence bands.

Bootstrap mediation results are reported in Table 4. The AIP→CX→PI path carried an indirect effect of 0.163 with a 95 % bootstrap interval that excluded zero ($CI_{0.95}$: [0.109, 0.223]); the CX→CL→PI path carried an indirect effect of 0.126 ($CI_{0.95}$: [0.080, 0.176]). Both

results support the stipulated mediation and confirm H5: customer loyalty is a significant partial mediator of the effect of customer experience on purchase intention.

Table 4. Bootstrap indirect effects (5,000 resamples).

Indirect path	Effect	LL 95 %	UL 95 %	Decision
AIP → CX → PI	0.163	0.109	0.223	Supported
CX → CL → PI	0.126	0.080	0.176	Supported

5. Discussion

Three substantive conclusions can be drawn. First, customer experience fully mediates the AI-driven personalisation → purchase intention relationship and is the single strongest predictor of purchase intention in the estimated model ($\beta = 0.245$). The findings thereby extend Hassan, Abdelraouf and El-Shihy (2025), who framed experience as a partial mediator, by showing that in a multi-channel digital context the experience channel predominates over the loyalty channel. This is consistent with the wider experiential view of consumer-AI interaction (Puntoni et al., 2021) and with field evidence from e-commerce (Davenport et al., 2020).

Second, customer loyalty carries its own direct effect on purchase intention ($\beta = 0.233$) that is statistically indistinguishable in magnitude from the experience effect, but explains a narrower slice of variance and only partially mediates the CX→PI relationship.

Loyalty in this dataset is an outcome of experience that adds cheer rather than substitutes. Marketers should accordingly treat experience and loyalty as complementary: neither operates in isolation, and investments that boost experience ripple down the loyalty→purchase intention chain.

Third, although privacy concerns depress purchase intention as a main effect ($\beta = -0.099$), the absence of an interaction effect indicates that the value of personalisation does not diminish with privacy concerns. Customers do not moderate the personalisation channel: they use it across the board, even when wary of data practices. This pattern reconciles two seemingly contradictory insights in the literature. Studies emphasising the paradox (Yildirim, 2026) focus on subjective discomfort with data collection, whereas studies emphasising AI effectiveness (Davenport et al., 2020) focus on the utility delivered. The present results suggest both can

coexist: privacy concerns damp desire to buy without offsetting the value of personalised delivery.

6. Implications

Theoretically, the study contributes a single, integrated structural model that simultaneously tests AI-driven personalisation, CX, CL, PI, privacy concerns and their interaction. It demonstrates that the S-O-R logic (Mehrabian & Russell, 1974) and the loyalty framework (Dick & Basu, 1994) can be combined productively, and that the personalisation-privacy paradox functions as a boundary condition on intention but not on the personalisation channel itself.

From a managerial perspective, the path coefficients imply a clear prioritisation. Improving the directional flow of personalisation has the largest payoff in the experiential layer, where firms should invest in real-time responsiveness, co-creative features and explainable recommendation systems (Huang & Rust, 2018). Investments in attitudinal loyalty through tiered programmes follow, while privacy concerns are best addressed by visible data practices and explicit consent policies, which protect the intention-to-buy bottom line without diluting personalisation value (Hermann et al., 2024).

7. Limitations and Future Research

Several limitations should be acknowledged. The cross-sectional design establishes associations but cannot directly resolve causal direction; experience and loyalty might in principle influence each other in the reverse order. Self-report data carry risks of common-method bias, although we took steps (counter-balanced item order, marker variables) to alleviate that concern. The sample, while broad, is drawn from a single national setting and may not generalise to high-involvement categories such as healthcare or financial services. Future research should pursue panel and experimental designs to verify the directionality, incorporate behavioural measures (click-streams, basket composition), and test the model in high-stakes contexts where AI mediates consequential decisions.

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