Artificial Intelligence in Retail Management: The Roles of Personalized Customer Experience and Customer Trust in Customer Loyalty

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This study examines the associations of personalized customer experience and customer trust with customer loyalty in artificial intelligence (AI)-enabled omnichannel retailing. An explanatory cross-sectional survey involved 300 modern retail consumers in Greater Tangerang, Indonesia, selected through purposive sampling with area quotas. Respondents had experienced digital retail services and observable forms of data-driven personalization. The data were analyzed using partial least squares structural equation modeling (PLS-SEM) in SmartPLS 4, supplemented by PLSpredict, the cross-validated predictive ability test (CVPAT), and multiple linear regression as a robustness check. Personalized customer experience was positively associated with customer loyalty ($\beta = 0.466$, $t = 10.59$, $p < 0.001$), as was customer trust ($\beta = 0.394$, $t = 8.57$, $p < 0.001$). Together, the predictors explained 59.8% of the variance in customer loyalty. All five loyalty indicators had positive Q^2_predict values, and CVPAT indicated lower predictive loss than the indicator-average and linear-model benchmarks. Regression results corroborated the directions of both relationships. The findings suggest that relevant, convenient, and consistent personalization and confidence in reliable, transparent data practices are complementary foundations of loyalty. Retailers should integrate customer-centric personalization with trustworthy data governance across omnichannel touchpoints. The cross-sectional, nonprobability design precludes causal inference and population-wide generalization.

Keywords: Artificial intelligence; Customer loyalty; Customer trust; Omnichannel retail; Personalized customer experience.

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1. Introduction

Digital transformation has shifted retail competition beyond transactional efficiency toward the capacity to manage adaptive, data-informed relationships across physical and digital channels. Artificial intelligence (AI) enables retailers to identify behavioral patterns, predict customer requirements, automate routine interactions, and tailor offerings to individual preferences. Strategic marketing research describes AI as a capability for segmentation, targeting, personalization, and relationship management, rather than merely an operational technology [1]. In retailing, its value arises through the interactions among algorithms, firms, employees, and customers [2]. AI applications include product recommendations, conversational assistance, personalized promotions, demand forecasting, and intelligent customer analytics; their value-creation mechanisms include automation, hyper-personalization, complementarity, and innovation [3]. However, a technically sophisticated recommendation does not necessarily translate into a positive

shopping experience. Consumers may welcome convenience and relevance yet resist automated interactions that appear intrusive, opaque, or restrictive of their control [4]. The pertinent managerial issue is therefore how technology-enabled services create experiences customers value and relationships they are willing to maintain.

This issue is particularly urgent in omnichannel retailing, where customers encounter the same retailer through stores, applications, websites, digital memberships, social media, payment systems, and customer-support channels. Customers evaluate the coherence of the entire journey rather than isolated transactions. A customer experience is accumulated across touchpoints before, during, and after purchase [5]. In AI-enabled settings, personalization involves matching recommendations, promotions, communication, and digital services to customer needs and prior interactions. Prior evidence identifies personalization and perceived convenience as significant components of AI-enabled customer experience [6], while research on digital experience design and smart retail emphasizes informative interaction, meaningful engagement, and intelligent service quality [7, 8]. At the same time, extensive reliance on customer data raises privacy and transparency concerns. The personalization–privacy paradox suggests that the same technologies that can support loyalty may create discomfort about data collection and use [9]. Accordingly, personalized experience and customer trust need to be considered jointly instead of treating technical personalization as a sufficient condition for loyalty.

Customer loyalty is strategically important because it encompasses repurchase intentions, retailer preference, positive recommendations, continued use of digital services, and reduced switching propensity. Trust is relevant to such intentions when customers cannot fully observe how their personal information is processed or how digital recommendations are generated. Evidence from online shopping identifies trust, experience, and branding as relevant antecedents of e-loyalty [10]; studies of AI-driven chatbots link service experience, perceived privacy risk, satisfaction, and continued use with subsequent loyalty intentions [11]. AI-chatbot service quality has also been associated with e-brand loyalty through users' trust and experience [12]. In omnichannel supermarkets, strategic digitalization and customer experience have been linked to loyalty [13], while automated retail studies highlight the relevance of customization and interactivity [14]. Yet these settings do not perfectly capture everyday omnichannel consumers who use both stores and retailer-managed digital services. This study therefore focuses on experienced modern retail shoppers in Greater Tangerang, covering Tangerang City, South Tangerang City, and Tangerang Regency, without restricting responses to a single retail brand.

The study aims to examine the respective associations of personalized customer experience (PCX) and customer trust (CT) with customer loyalty (CL) in the context of AI-enabled modern retail management. AI is treated as the service context observable through data-driven promotions, recommendation systems, digital memberships, chatbots, and related services, not as a separate latent variable presumed to be technically understood by respondents. PCX captures perceived relevance, convenience, and cross-channel consistency; CT captures perceived reliability, data security, transparency, and responsible use of personalization. A cross-sectional sample of 300 consumers is analyzed using PLS-SEM with predictive and regression-based sensitivity assessments. By examining these two relational foundations in parallel, the study contributes an integrated account of experiential value and relational assurance in omnichannel loyalty. The results are intended to inform more transparent and customer-centered personalization practices, while remaining subject to the inferential limitations of a nonprobability cross-sectional design.

2. Literature Review And Problem Statement

Personalized customer experience integrates individual relevance with the continuity of the customer journey. It is not equivalent to the provision of generic digital functionality: recommendations and offers must correspond to customer preferences, shopping history, and the context in which they are received. Studies of customer experience management and journey design emphasize the importance of coherent interactions across multiple touchpoints [15, 16]. Data-enabled relationship management may improve the precision of customized services [17], and AI-supported shopping encounters have been connected with engagement and digitally enriched experience [18]. In the present model, PCX is operationalized through the perceived relevance of recommendations and offers, responsiveness of digital services to prior interactions, consistency between physical and digital channels, and greater convenience in shopping. These attributes can support repeat choice and preference by reducing search effort and improving contextual fit. Based on these arguments, H1 states that personalized customer experience is positively associated with customer loyalty in AI-enabled omnichannel retailing.

Customer trust is the belief that a retailer and its digital services are reliable, competent, safe, transparent, and attentive to customers' interests. This dimension differs from the immediate usefulness of personalized services: consumers can value a recommendation while remaining uncertain about the retailer's information practices. Research on AI service agents links satisfaction to intentions to continue use [19], while chatbot studies show that conversational design and user interaction can shape service responses [20]. Humanlike conversational warmth and competence may enhance chatbot effectiveness under particular conditions [21], and a meta-analysis of AI-enabled virtual assistants identifies the joint importance of technology, user, and situational characteristics [22]. The personalization–privacy paradox explains why heightened customization can simultaneously produce value and perceived risk [9]. Research on personalized recommendations in AI-driven e-commerce further connects personalization with the trust–satisfaction–loyalty relationship [23]. Accordingly, H2 states that customer trust is positively associated with customer loyalty in AI-enabled omnichannel retailing.

Three research gaps motivate the integrated model. First, research on AI in retailing has addressed technological acceptance, chatbot quality, customer journeys, automated stores, and loyalty, but provides less directly comparable evidence on PCX and CT as two simultaneous predictors of loyalty among everyday omnichannel shoppers. Second, the benefits of personalization coexist with relational and privacy risks, so personalization cannot be presumed to translate unconditionally into sustained loyalty. Third, evidence obtained in e-commerce, chatbots, luxury retail, shopping malls, and fully automated stores cannot automatically be generalized to modern retailers offering both physical and digital touchpoints. The present study evaluates two direct paths, PCX → CL (H1) and CT → CL (H2), in a common structural model. The analysis does not specify CT as a mediator or moderator, or estimate a separate effect of AI adoption. The research problem is whether both experiential personalization and relational confidence retain positive, statistically distinguishable associations with loyalty when considered together in a defined omnichannel retail context.

3. Method

Research Design and Setting

A quantitative explanatory, cross-sectional design was used to evaluate the hypothesized relationships among PCX, CT, and CL. The unit of analysis was an individual consumer, rather than a retail company or brand. The setting was Greater Tangerang, Banten Province, comprising Tangerang City, South Tangerang City, and Tangerang Regency. AI was operationalized as the context of consumer-facing, data-driven retail services, such as recommendations, personalized promotions, digital memberships, chatbots, transaction reminders, and adaptive communications. The research model assessed customer perceptions of these services, not the technical sophistication of the underlying algorithms. This distinction was maintained throughout measurement, analysis, and interpretation.

Population, Sampling, and Eligibility

The target population comprised consumers of modern omnichannel retailers in Greater Tangerang. As no complete sampling frame of individuals exposed to relevant personalized retail services was available, a nonprobability purposive strategy was combined with operational area quotas. The target was 300 usable responses, approximately 100 in each of the three local jurisdictions. The quota served to maintain geographic spread and was not interpreted as proportional representation of the area's population. The sample-size rationale specified two predictors, a medium effect size ($f^2 = 0.15$), a 5% significance level, and 95% statistical power, yielding an estimated minimum requirement of approximately 107 observations; the target sample exceeded this threshold.

Eligible respondents had to be at least 17 years old; live, work, study, or regularly engage in activities in Greater Tangerang; have purchased from a modern retailer with physical and digital channels within the preceding six months; have used at least one digital retail channel; and have experienced at least two observable types of personalization, such as tailored recommendations, individualized promotions, transaction reminders, or adaptive chat services. Individuals whose exposure was limited to conventional in-store shopping without digital services were screened out. Each participant was instructed to assess one reference retailer: the omnichannel retailer most frequently used together with its digital channel during the previous six months. This instruction was intended to avoid combining impressions from different brands in a single response.

Instruments and Operationalization

Primary data were obtained using a structured questionnaire with five-point agreement responses ranging from 1 (strongly disagree) to 5 (strongly agree). All three latent constructs were specified as reflective and assessed using five indicators each. Indicators were contextually adapted from established research on AI-enabled experience, digital customer trust, and loyalty. Table 1 summarizes their operational definitions, indicator domains, and principal sources.

Table 1. Operationalization of the study constructs

Construct	Operational definition	Measurement indicators	Main sources
Personalized Customer	Perceived relevance, needs alignment, convenience, and cross-	PCX1 relevant product recommendations; PCX2 suitable promotions/vouchers; PCX3 services adapted to prior interactions; PCX4 consistent	[6, 7, 8]

Construct	Operational definition	Measurement indicators	Main sources
Experience (PCX)	channel consistency of retail experiences enabled by data-driven/AI services.	physical–digital personalization; PCX5 greater ease and shopping value.	
Customer Trust (CT)	Confidence that the retailer and its digital services are competent, reliable, secure, transparent, and responsible in their use of data.	CT1 service reliability; CT2 credible information/recommendations; CT3 secure management of customer data; CT4 transparent explanation of data use; CT5 responsible personalization.	[6, 10, 12]
Customer Loyalty (CL)	Attitudinal and behavioral commitment reflected in repurchase, preference, advocacy, continued digital use, and lower switching inclination.	CL1 repurchase intention; CL2 first-choice retailer; CL3 recommendation intention; CL4 intention to keep using digital/membership channels; CL5 resistance to switching.	[10, 11, 13, 12]

Before the main survey, the questionnaire was pilot-tested with approximately 30 eligible individuals not included in the analytical sample. The pilot examined item wording, readability, the comprehensibility of AI-enabled service examples, completion time, and preliminary internal consistency. Ambiguous items were revised without changing their substantive domains. The survey opened with short explanations of observable personalization services so that respondents evaluated their own experiences rather than inferring retailers' undisclosed back-end technology.

Data Collection, Quality Control, and Ethical Safeguards

The questionnaire was distributed through online and offline channels using electronic forms or QR codes. Respondents first completed eligibility screening and identified one reference retailer for all subsequent items. Participation was voluntary; names and other direct personal identifiers were not collected, and respondents received information about the academic purpose of the study. To mitigate common method bias, the questionnaire used concise, non-leading statements, avoided prominently labeling constructs, and emphasized that there were no correct or incorrect answers. Records were screened for ineligible exposure, duplicate submissions, implausible response patterns, and completion times too short for meaningful item reading.

Structural Model and Analysis Procedures

Partial least squares structural equation modeling (PLS-SEM) was implemented in SmartPLS 4 to estimate latent constructs and examine direct relationships with customer loyalty. The model contained the paths PCX → CL and CT → CL and did not include mediation, moderation, or a separate AI construct. Its structural equation was $CL = \beta_1 PCX + \beta_2 CT + \zeta$, where β_1 and β_2 represent standardized structural coefficients and ζ

represents the disturbance term. H1 and H2 were assessed using the sign and statistical precision of their respective direct coefficients at $\alpha = 0.05$.

First, reflective measurement quality was assessed using outer loadings (target ≥ 0.708), Cronbach's alpha, rho_A, composite reliability (preferred 0.70–0.95), average variance extracted (AVE ≥ 0.50), and the heterotrait–monotrait ratio (HTMT; stringent threshold < 0.85). Indicators with loadings between 0.40 and 0.70 would be considered for removal only when this improved measurement quality without compromising content validity. Second, structural evaluation considered inner variance inflation factors (VIF; preferably < 3), standardized path coefficients, two-sided bootstrap confidence intervals, significance values, R^2, adjusted R^2, and f^2 effects. The bootstrap procedure used 5,000 subsamples at the 5% significance level, with f^2 values of approximately 0.02, 0.15, and 0.35 representing small, medium, and large effects.

Third, predictive performance was evaluated with PLSpredict using 10-fold cross-validation repeated 10 times. Indicator-level Q^2_predict values assessed prediction relative to the indicator-average benchmark; root mean square error (RMSE) and mean absolute error (MAE) were compared with a linear-model (LM) benchmark. The cross-validated predictive ability test (CVPAT) provided a statistical comparison of average predictive loss against indicator average and LM predictions. Descriptive summaries covered demographics, retailer categories, usage frequency, channels, and forms of personalization. Finally, regression of composite CL scores on PCX and CT was used as a robustness check. Because the survey was cross-sectional and nonprobability-based, relationships were interpreted as associations rather than identified causal effects.

4. Results And Discussion

Respondent Characteristics and Omnichannel Exposure

A total of 326 questionnaires were initially received. Screening excluded 17 respondents who lacked the required digital personalization experience, five duplicate records, and four responses exhibiting inadequate completion patterns. The resulting analytical sample comprised 300 usable records, with 100 respondents from each study area. Table 2 presents the sample profile and digital channel use frequency; the balanced geographical quotas do not indicate an equivalent population distribution.

Table 2. Respondent characteristics and omnichannel retail use

Characteristic	Category	n	%
Area	Tangerang City	100	33.3
	South Tangerang City	100	33.3
	Tangerang Regency	100	33.3
Gender	Male	134	44.7
	Female	166	55.3
Age	17–24 years	94	31.3
	25–34 years	109	36.3
	35–44 years	59	19.7
	45 years or older	38	12.7
Reference retailer	Minimarket	123	41.0
	Supermarket	84	28.0

Characteristic	Category	n	%
	Hypermarket	54	18.0
	Department/specialty retailer	39	13.0
Digital channel use	2–3 times/month	81	27.0
	4–6 times/month	102	34.0
	7–10 times/month	65	21.7
	More than 10 times/month	52	17.3

The largest age group was 25–34 years (36.3%), followed by 17–24 years (31.3%). Minimarkets were the most frequently selected reference retailers (41.0%), while supermarkets, hypermarkets, and specialty retailers remained represented. A majority of participants reported using retail digital channels at least four times per month. This experience provided an appropriate basis for assessing perceived personalization, trust, and loyalty toward a defined retailer, although it does not establish representativeness across all retail customers.

Table 3. Digital channels and forms of personalization experienced

Category	Experienced channel or service	n	% of respondents
Digital channels	Retailer application	242	80.7
	Digital membership program	213	71.0
	Retailer website	116	38.7
	Chatbot/conversational service	87	29.0
Personalization	Personalized promotions/vouchers	254	84.7
	Product recommendations	225	75.0
	Transaction reminders/offers	157	52.3
	Adaptive chatbot/communication	95	31.7

Note: Multiple responses were permitted; percentages within the same group do not sum to 100%.

Retailer applications were the most common digital touchpoint (80.7%), followed by digital membership programs (71.0%). Personalized promotions and vouchers (84.7%) and product recommendations (75.0%) were the most frequently encountered forms of personalization. These exposures are consistent with the service-based operational definition of the AI-enabled retail context; respondents were not asked to verify whether each individual service relied on a particular machine-learning architecture.

Descriptive Statistics

Table 4. Descriptive statistics for the research constructs

Construct	Mean	SD	Minimum	Maximum
Personalized Customer Experience (PCX)	3.94	0.58	2.20	5.00
Customer Trust (CT)	3.98	0.61	2.00	5.00
Customer Loyalty (CL)	4.02	0.59	2.20	5.00

The mean scores of all three constructs were relatively high on the five-point response scale. CL had the highest mean (4.02), followed by CT (3.98) and PCX (3.94). Standard deviations ranged from 0.58 to 0.61, suggesting variation in consumer responses without all observations being concentrated in one response category. These summaries characterize the sample and do not imply causal or population-level differences among the latent constructs.

Reflective Measurement Model and Discriminant Validity

All 15 reflective indicators had loadings above 0.70, and no indicator was removed from the specification. Cronbach's alpha, rho_A, and composite reliability were within the predetermined acceptable range, while all AVE values exceeded 0.50. Table 5 reports indicator loadings and construct-level measurement quality, preserving the results in the original manuscript.

Table 5. Reflective measurement reliability and convergent validity

Construct	Indicator	Loading	Alpha	rho_A	CR	AVE
PCX	PCX1	0.812	0.885	0.889	0.916	0.687
	PCX2	0.846				
	PCX3	0.831				
	PCX4	0.795				
	PCX5	0.858				
CT	CT1	0.823	0.895	0.897	0.923	0.705
	CT2	0.861				
	CT3	0.842				
	CT4	0.817				
	CT5	0.854				
CL	CL1	0.846	0.901	0.903	0.927	0.718
	CL2	0.878				
	CL3	0.831				
	CL4	0.812				
	CL5	0.867				

Composite reliability ranged from 0.916 to 0.927, and AVE ranged from 0.687 to 0.718. These values support internal consistency and convergent validity for all three reflective constructs. In addition to evaluating each latent variable separately, the analysis assessed whether the conceptually related perceptions of personalization, trust, and loyalty remained empirically distinct.

Table 6. Heterotrait–monotrait ratios (HTMT)

Construct	PCX	CT	CL
PCX	—		
CT	0.736	—	
CL	0.806	0.781	—

The highest HTMT was observed between PCX and CL (0.806), followed by CT and CL (0.781) and PCX and CT (0.736). Each value was below 0.85, supporting discriminant validity under the criterion specified in the method. The constructs can therefore be treated as related but nonidentical dimensions of the customer relationship, rather than interchangeable measures.

Structural Model and Hypothesis Tests

The inner VIF values for both predictors were 1.55, indicating no serious structural collinearity. The model explained 59.8% of the variance in customer loyalty ($R^2 = 0.598$; adjusted $R^2 = 0.595$). The bootstrap results in Table 7 show that both hypothesized direct associations were positive and statistically significant.

Table 7. Structural path estimates and hypothesis decisions

Hyp.	Path	β	SE	t	p	95% CI	f²	Decision
H1	PCX → CL	0.466	0.044	10.59	<0.001	[0.378, 0.550]	0.284	Supported
H2	CT → CL	0.394	0.046	8.57	<0.001	[0.303, 0.481]	0.204	Supported

PCX was positively associated with CL (β = 0.466, t = 10.59, p < 0.001, 95% CI [0.378, 0.550]), with a medium-sized f² effect of 0.284. Therefore, H1 was supported. This association indicates that consumers reporting more relevant recommendations, better-targeted promotions, greater digital convenience, and more consistent cross-channel personalization also tended to report higher loyalty toward their reference retailer. CT was also positively associated with CL (β = 0.394, t = 8.57, p < 0.001, 95% CI [0.303, 0.481]), with f² = 0.204; hence, H2 was supported. PCX had a numerically larger standardized coefficient than CT, but the study did not conduct a formal test of the difference between these coefficients. Accordingly, their relative magnitude is interpreted descriptively, not as proof that one association is statistically stronger than the other.

Out-of-Sample Predictive Assessment

PLSpredict was conducted with 10-fold cross-validation repeated 10 times. All five customer loyalty indicators yielded positive Q²_predict statistics, indicating better prediction than the indicator-average benchmark. PLS-SEM achieved lower RMSE and MAE than the linear-model benchmark for four of the five indicators; CL4 was the exception. This pattern suggests moderate-to-good predictive performance under the evaluation design specified in the study.

Table 8. PLSpredict statistics for customer loyalty indicators

Indicator	Q²_predict	RMSE PLS	RMSE LM	MAE PLS	MAE LM
CL1	0.421	0.598	0.612	0.465	0.476
CL2	0.447	0.571	0.589	0.439	0.451
CL3	0.392	0.627	0.639	0.481	0.489
CL4	0.365	0.651	0.646	0.501	0.498
CL5	0.413	0.604	0.619	0.463	0.474

Table 9. Cross-validated predictive ability test (CVPAT)

Comparison	Difference in average loss	p-value	Interpretation
PLS-SEM vs. indicator average (IA)	−0.145	<0.001	Lower PLS-SEM predictive loss
PLS-SEM vs. linear model (LM)	−0.018	0.028	Lower PLS-SEM predictive loss

The CVPAT findings supported the indicator-level comparisons. PLS-SEM showed lower average predictive loss than the indicator-average model (difference = −0.145, p < 0.001) and the linear model (difference = −0.018, p = 0.028). These negative and statistically significant differences support the model's relative predictive performance for CL within the cross-validation procedure. Predictive superiority in these data should not be conflated with causal identification or automatic transportability to other populations, retailers, or regions.

Regression Robustness Check and Hypothesis Summary

As a robustness assessment, composite scores of PCX and CT were used in a multiple linear regression predicting CL. The estimated standardized coefficients maintained the positive directions and ordering found in the PLS-SEM model. The regression explained 55.1% of the observed variation in CL ($R^2 = 0.551$; adjusted $R^2 = 0.548$), slightly less than the reported PLS-SEM R^2 but consistent with the same substantive pattern.

Table 10. Multiple regression robustness estimates

Predictor	Standardized β	t	p-value	VIF
Personalized Customer Experience	0.452	9.24	<0.001	1.51
Customer Trust	0.382	7.82	<0.001	1.51

Table 11. Summary of hypothesis decisions

Hypothesis	Statement	Result
H1	Personalized customer experience is positively associated with customer loyalty.	Supported
H2	Customer trust is positively associated with customer loyalty.	Supported

The convergence of PLS-SEM and linear regression results supports the stability of the reported positive associations across two estimation procedures, without establishing causality. Table 11 confirms that both original hypotheses were supported; no mediation, moderation, or direct AI adoption hypotheses were evaluated.

Personalized Customer Experience and Customer Loyalty

The positive PCX–CL association supports the view that loyalty is not determined by an AI label but by customers' actual experiences of service relevance, ease, and continuity. Customers appear more likely to favor a retailer when product suggestions and promotions address their needs, digital interactions reduce unnecessary effort, and experiences remain coherent across physical and online channels. This pattern is consistent with the understanding of customer experience as an accumulated evaluation of interactions throughout the journey [5]. Research on customer experience management and journey design likewise emphasizes the strategic role of coherent touchpoint encounters [15, 16]. The medium f^2 estimate for PCX (0.284) and its larger numerical path coefficient in the present model support attention to personalization as one relational basis for loyalty, although they do not demonstrate a statistically significant advantage over trust.

The substantive value of personalization arises when the retailer translates information into reduced search effort, greater relevance, and more convenient choices. Digital experience research emphasizes that informational and interactive benefits depend on design quality [7], while large-scale customer data can support service customization [17]. Prior AI-enabled experience research identifies personalization and convenience as key dimensions of consumers' evaluations [6], and research on intelligent retail encounters relates such experience quality to engagement [8]. Therefore, the PCX relationship can be understood as a connection between the perceived usefulness of customized retail interaction and willingness to maintain a relationship, rather than an assertion that personalization technology directly causes repeat purchase.

Omnichannel continuity gives this relationship particular significance. A retailer might offer a personalized voucher in its application but fail to recognize it in the physical store, or recommend items inconsistent with transaction history; either failure would weaken the coherence of the experience. Prior evidence concerning omnichannel supermarket loyalty [13] and AI-powered automated stores [14] provides relevant context for the importance of integrated service design. Research on AI-enhanced luxury shopping experiences further illustrates the role of digital engagement and service cues [18]. The present sample extends the discussion to more everyday forms of modern retail, where applications, memberships, offers, and routine store visits coexist. The managerial lesson is to assess AI investment against consumers' perceived relevance, convenience, cross-channel continuity, and practical value, not solely against technical performance indicators.

Customer Trust and Loyalty in AI-Enabled Retail

The CT–CL coefficient ($\beta = 0.394$; $f^2 = 0.204$) indicates that perceived retailer reliability, competence, security, transparency, and responsible personalization are positively associated with loyalty even when PCX is considered simultaneously. This aligns with evidence that trust is relevant to loyalty in digital shopping environments characterized by uncertainty and information asymmetry [10]. In AI-enabled personalization, customers often cannot directly observe how much data are collected, which inferences are produced, or how recommendations are prioritized. The personalization–privacy paradox highlights that useful individualized services can nevertheless trigger discomfort about data practices [9], and the experiential perspective on AI stresses the coexistence of benefits and concerns about control and agency [4]. Trust therefore constitutes a relational condition complementary to the usefulness of personalization.

Evidence from conversational AI helps interpret the role of trust. Research on chatbots identifies both gratifications and perceived privacy risk as relevant to satisfaction and continued engagement [11], while AI-chatbot service quality has been connected with e-brand loyalty through trust and user experience [12]. Other studies indicate that satisfaction, interaction design, and the social characteristics of AI assistance can shape users' willingness to continue relying on automated services [19, 20, 21]. A meta-analysis of retail virtual assistants also suggests that successful deployment depends on technology, consumer, and contextual factors rather than technology alone [22]. In practical terms, responsive and intelligible service interactions, predictable performance, credible safeguards, and a readily accessible human escalation route may help retailers maintain confidence in AI-supported service delivery.

Research on AI-driven e-commerce suggests that personalized recommendations may condition the trust–satisfaction–loyalty relationship [23]. The present model did not test a moderation or mediation pathway, so that mechanism cannot be claimed as empirically established here. Instead, the findings support a more limited but useful conclusion: trust and perceived experience each show their own positive direct association with loyalty in the specified sample. Retailers should therefore not treat trust as a secondary compliance issue. Clear consent options, data-use explanations, security assurances, preference controls, accurate recommendations, and dependable service recovery should be considered elements of the customer experience itself.

Explanatory Power, Predictive Consistency, and Model Interpretation

PCX and CT jointly accounted for 59.8% of the variance in CL within the PLS-SEM model. This substantive explanatory share aligns with the strategic view of AI as a capability for customer sensing, personalization,

and relationship management [1] and with retail value-creation accounts emphasizing hyper-personalization and complementary service capabilities [3]. At the same time, this R^2 represents the fitted model in a nonprobability cross-sectional sample, not a universal percentage of loyalty determined by the two constructs. Predictive evaluation adds a distinct perspective: positive Q^2_predict for all five CL indicators, benchmark advantages for four of five indicators, and significant CVPAT comparisons indicate promising performance within the particular cross-validation design. These findings support prediction under the tested conditions, rather than proof that the specified relationships generalize automatically to every retailer or consumer population.

The regression robustness check strengthens confidence in the reported directional patterns. Both PCX and CT remained positive, statistically significant predictors in the composite-score specification, with coefficients of 0.452 and 0.382, respectively, and R^2 = 0.551. AI-enabled customer relationship management has been described as a reconfiguration of how firms learn from, target, and serve customers [24], while broader retail scholarship cautions that organizational processes, frontline employees, and digital technologies must be coordinated in service delivery [2]. Research has also associated AI and employee service quality with satisfaction and loyalty [25]. These insights support a hybrid-service interpretation: automation may personalize routine interactions, while human support remains important for empathy, explanation, complaints, and complex needs. None of these interpretations requires assuming that consumers know the algorithmic details of the retailer's systems.

Theoretical and Managerial Implications

Theoretically, the findings integrate AI-enabled customer experience with relationship marketing by distinguishing experiential value from relational assurance. PCX concerns the relevance, convenience, and coherence of personalized encounters, while CT concerns perceived security, integrity, and dependability in the same relationship. The constructs were empirically distinguishable (HTMT between PCX and CT = 0.736) and both were associated with CL when entered simultaneously. This supports the analytical usefulness of viewing AI-assisted loyalty through two complementary lenses. It does not support causal assertions about the sequence in which experience and trust develop, nor does it demonstrate that one coefficient is statistically stronger than the other.

Managerially, the high reported use of retailer applications (80.7%), digital memberships (71.0%), personalized promotions (84.7%), and recommendations (75.0%) suggests that service orchestration may be more important than merely adding digital channels. Retailers can prioritize a unified, responsibly managed customer data architecture that preserves consistency across stores, applications, and membership systems. Personalization should be understandable and controllable, allowing customers to adjust preferences and recognize why relevant offers appear. Conversational assistants should be designed for competence and appropriate social responsiveness, with seamless escalation to human staff where automation is inadequate. These priorities reflect the original study's emphasis on customer relevance, convenience, continuity, data security, transparency, and service integrity rather than on algorithmic sophistication alone.

At the relationship-strategy level, privacy-by-design, transparent data practices, proportionate personalization, clear consent procedures, and explainable recommendations are pertinent safeguards. More intensive personalization should not be pursued at the expense of consumer autonomy or confidence. The study's results can guide retail managers in monitoring experiential and trust-related indicators

separately, along with repurchase intention, preference, advocacy, and digital-channel continuity. Future research should test whether privacy concern, perceived control, satisfaction, AI literacy, or technology readiness moderates or mediates these relationships and whether results remain stable across retailers, regions, and longitudinal observation periods. Such extensions are needed because the present design tests direct associations in one cross-sectional sample, not a full mechanism of loyalty formation.

5. Conclusion

This study identified two positive, statistically significant associations with customer loyalty among 300 omnichannel retail consumers in Greater Tangerang. Personalized customer experience was positively related to loyalty ($\beta = 0.466$, $p < 0.001$), and customer trust showed an additional positive relationship ($\beta = 0.394$, $p < 0.001$). The joint model accounted for 59.8% of the observed variance in customer loyalty. Although PCX had the numerically larger coefficient, the difference in path strengths was not formally tested; therefore, the findings support the importance of both constructs rather than a conclusive ranking of their effects.

The measurement evaluation supported reliability, convergent validity, and discriminant validity of the three reflective constructs. PLSpredict and CVPAT suggested favorable out-of-sample performance under the implemented validation procedure, and multiple regression maintained the positive directions of the main relationships. Together, these results are consistent with the proposition that loyalty in AI-enabled omnichannel retailing is associated not only with tailored, convenient, and coherent experiences but also with perceived integrity, security, and transparency in retailer–customer interactions. Accordingly, retailers should combine relevant, cross-channel personalization with responsible data governance and dependable human support when necessary.

Several limitations qualify these conclusions. The cross-sectional design cannot establish temporal or causal ordering, the purposive area-quota sample cannot be assumed to represent all consumers in Greater Tangerang, and the questionnaire measures consumer perceptions of observable services rather than independently auditing the AI technology in each retailer. Future studies should use longitudinal or experimental designs, broaden the retailer types and geographic settings, and consider privacy concern, perceived control, satisfaction, AI literacy, and technology readiness as potential boundary conditions or intervening mechanisms. The present contribution is therefore an integrated associative and predictive assessment of experience and trust as complementary correlates of customer loyalty.

6. References

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