



Intelligent Customer Relationship Management in the Platform Economy: The Interplay of AI Personalization, Customer Experience, Trust, and Loyalty

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Peer Review Information	Abstract
<i>Submission: 21 Jan 2020</i> <i>Revision: 06 Feb 2020</i> <i>Acceptance: 21 March 2020</i> Keywords <i>AI personalization,</i> <i>Customer experience, Trust,</i> <i>Customer loyalty, Platform</i> <i>economy</i>	The platform economy has intensified the use of algorithmic intermediation, data analytics, and artificial intelligence (AI) in customer relationship management. This methodology paper develops an empirically testable framework for intelligent customer relationship management (iCRM) by examining the interplay among AI personalization, customer experience, trust, and customer loyalty. Drawing on customer relationship management, digital platform, online customer experience, personalization-privacy, and trust-loyalty research published in 2020 or earlier, the study proposes a quantitative cross-sectional design for users of digital platforms such as e-commerce, mobility, food-delivery, travel, and digital-service applications. The model treats AI personalization as a technology-enabled relational stimulus that can improve relevance and convenience, customer experience as an evaluative response to the platform journey, trust as a key relational mechanism under uncertainty, and loyalty as the focal behavioral outcome. The proposed study uses a structured questionnaire, multi-item Likert scales, and partial least squares structural equation modeling (PLS-SEM) to assess measurement quality, direct effects, mediation, and predictive power. Because this paper is methodological and no original field dataset is supplied, the Results section reports expected analytical patterns and a transparent reporting template rather than fabricated coefficients. The framework offers a rigorous basis for evaluating how platform firms can use AI-enabled CRM to create personalized experiences while maintaining trust and long-term customer relationships.

Introduction

Digital platforms have reshaped the organization of markets by connecting multiple participant groups, coordinating transactions, and continuously learning from user interactions. Platform businesses are not simply online channels; they are socio-technical infrastructures in which data, algorithms, network effects, governance rules, and user interfaces jointly influence value creation. de Reuver, Sørensen, and Basole (2018) emphasize that digital platforms require research attention

beyond conventional information systems because their architecture and ecosystem relationships create distinctive managerial challenges. McIntyre and Srinivasan (2017) similarly show that platform strategy is closely connected with network structures and feedback effects. Within this setting, customer relationship management increasingly depends on the ability of firms to interpret large volumes of behavioral data and convert those data into relevant, timely, and consistent interactions.

Traditional customer relationship management (CRM) conceptualizes relationship building as a cross-functional process integrating strategy, value creation, multichannel integration, information management, and performance assessment (Payne & Frow, 2005). The platform economy extends this logic because customer interactions occur across many digital touchpoints and generate real-time signals that can be analyzed at scale. AI technologies strengthen this capability by supporting prediction, classification, recommendation, automated service, conversational interaction, and adaptive personalization. Huang and Rust (2018) explain that AI in service can perform mechanical, analytical, intuitive, and, increasingly, empathetic tasks. Davenport, Guha, Grewal, and Bressgott (2020) further argue that AI will alter marketing strategy and customer behavior while creating important questions regarding privacy, bias, ethics, and human augmentation.

A central promise of intelligent CRM is personalization. Platforms can use browsing history, past purchases, search behavior, location signals, ratings, clickstreams, and other behavioral indicators to tailor recommendations, communication, offers, and service interfaces. Personalization can reduce search costs and increase perceived relevance; however, it also raises questions about how data are collected and used. Aguirre, Mahr, Grewal, de Ruyter, and Wetzels (2015) describe this tension as a personalization paradox: personalization can improve response when information collection is transparent, yet covert or unexpected data use can create vulnerability and reduce effectiveness. Martin and Murphy (2017) likewise position privacy as a major marketing issue because consumer trust depends not only on service performance but also on perceived fairness and control over personal information. Bandara, Fernando, and Akter (2020) show that privacy concerns in e-commerce are multidimensional and remain central to consumer behavior in data-intensive environments.

Customer experience provides the experiential bridge between AI-enabled platform capabilities and relationship outcomes. Lemon and Verhoef (2016) define customer experience as a broad response to interactions across the customer journey, involving multiple touchpoints and actors. Rose, Clark, Samouel, and Hair (2012) demonstrate that online customer experience influences satisfaction and behavioral outcomes, while Bleier, Harmeling, and Palmatier (2019) show that design elements can shape informativeness, entertainment, social presence,

and sensory appeal. In AI-enabled settings, Prentice, Weaven, and Wong (2020) report a chain linking perceptions of AI service performance, satisfaction, and customer engagement, indicating that AI quality becomes meaningful when it improves the user's lived service experience.

Trust is especially important in platform environments because transactions often involve information asymmetry, perceived risk, algorithmic opacity, and limited face-to-face interaction. Gefen, Karahanna, and Straub (2003) established that trust complements technology acceptance in online shopping. Sirdeshmukh, Singh, and Sabol (2002) link trust with customer value and loyalty in relational exchanges. In electronic commerce, loyalty reflects repeat patronage, preference, resistance to switching, and positive advocacy; Srinivasan, Anderson, and Ponnnavolu (2002) identify several antecedents of e-loyalty, including customization and interactivity. These streams suggest that AI personalization may strengthen loyalty, but the effect is unlikely to be purely technological: customers must first perceive a superior experience and remain confident that the platform is reliable, competent, benevolent, and responsible in its use of data.

The present methodology paper therefore proposes an integrated iCRM model for the platform economy. The model asks whether AI personalization improves customer experience and trust, whether customer experience strengthens trust, and whether customer experience and trust translate into loyalty. It also permits examination of indirect effects, particularly whether customer experience and trust mediate the association between AI personalization and loyalty. By integrating CRM, customer journey, trust, personalization-privacy, AI service, and platform research, the study provides a research design that can be implemented empirically without overstating evidence that has not yet been collected.

Literature Review

1. Intelligent CRM and the platform economy

Payne and Frow (2005) move CRM beyond a software-centered interpretation and frame it as a strategic, cross-functional process for creating value through integrated customer information and interactions. This perspective is particularly relevant to platform firms because data generated by one touchpoint can influence decisions at other touchpoints. Platform research adds a structural dimension: digital platforms

coordinate users, complementors, data, and services through shared technological architectures and governance mechanisms (de Reuver et al., 2018). Network-oriented strategy research also shows that platform value can grow as participant networks expand and interaction density increases (McIntyre & Srinivasan, 2017). Intelligent CRM can therefore be understood as the application of AI-enabled analytical and interaction capabilities to CRM processes within a platform ecosystem.

2. AI personalization

AI personalization refers to the algorithmic adaptation of content, recommendations, communication, offers, or service features using individual- or segment-level data. Huang and Rust (2018) explain how AI can automate analytical service tasks and progressively support more complex service decisions. Davenport et al. (2020) identify targeting, recommendation, prediction, and customer interaction as important marketing applications of AI. Yet personalization effectiveness depends on how customers interpret the underlying information collection. Aguirre et al. (2015) demonstrate that transparent information collection and trust-building strategies can mitigate negative reactions associated with personalized advertising. Thus, AI personalization is expected to improve relevance and convenience, but its relational value depends on a trustworthy platform context.

3. Customer experience

Customer experience captures cognitive, emotional, behavioral, sensory, and social responses arising across the customer journey. Lemon and Verhoef (2016) emphasize that experience develops over time and across pre-purchase, purchase, and post-purchase stages. Rose et al. (2012) provide empirical evidence that online experience is associated with important outcomes such as satisfaction and

repurchase intentions. Bleier et al. (2019) show that different online design choices affect distinct experience dimensions and that their effectiveness depends on product and brand conditions. In iCRM, personalization should enhance experience when recommendations are accurate, useful, timely, and easy to act upon.

4. Trust

Trust reduces uncertainty when customers cannot fully observe the intentions or capabilities of a digital seller or platform. Gefen et al. (2003) show that trust is a core determinant of online shopping behavior alongside perceived usefulness and ease of use. Sirdeshmukh et al. (2002) conceptualize trust as an important mechanism through which service-provider behavior affects perceived value and loyalty. For AI-enabled platforms, trust also incorporates beliefs about data security, privacy, algorithmic reliability, and appropriate use of personal information. Martin and Murphy (2017) and Bandara et al. (2020) demonstrate why privacy governance is inseparable from trust in data-intensive marketing.

5. Customer loyalty

Customer loyalty in digital markets includes repeated use, continued patronage, positive recommendation, preference, and resistance to switching. Srinivasan et al. (2002) show that customization and interactivity are among the drivers of e-loyalty. Sirdeshmukh et al. (2002) link trust and value to loyalty, suggesting that loyalty results from accumulated relational evaluations rather than isolated transactions. In platform contexts, loyalty is strategically important because users can often switch among competing apps with low procedural effort. The proposed model therefore treats loyalty as the ultimate relational consequence of successful AI personalization, positive customer experience, and trust.

6. Synthesis of prior literature

Table 1: Summary of Key Literature and Contributions Relevant to the Study

Study	Year	Primary focus	Key contribution to this paper	DOI
Payne & Frow	2005	Strategic CRM	Frames CRM as integrated, cross-functional relationship management.	10.1509/jmkg.2005.69.4.167
Srinivasan et al.	2002	E-loyalty	Shows customization/interactivity as antecedents of loyalty.	10.1016/S0022-4359(01)00065-3
Gefen et al.	2003	Online trust	Establishes trust as central to online adoption and transactions.	10.2307/30036519

Aguirre et al.	2015	Personalization paradox	Shows personalization works better when data collection is transparent.	10.1016/j.jretai.2014.09.005
Lemon & Verhoef	2016	Customer journey	Defines experience across multiple touchpoints and stages.	10.1509/jm.15.0420
McIntyre & Srinivasan	2017	Platform strategy	Connects platform competition with networks and strategic feedback effects.	10.1002/smj.2596
Huang & Rust	2018	AI in service	Explains AI capabilities and service-task substitution/augmentation.	10.1177/1094670517752459
de Reuver et al.	2018	Digital platforms	Provides a research agenda for platform architectures and ecosystems.	10.1057/s41265-016-0033-3
Bleier et al.	2019	Online experience	Shows design choices shape online experience dimensions.	10.1177/0022242918809930
Davenport et al.	2020	AI in marketing	Explains AI effects on marketing strategy, consumers, privacy, and ethics.	10.1007/s11747-019-00696-0
Prentice et al.	2020	AI service quality	Links AI quality, satisfaction, and customer engagement.	10.1016/j.ijhm.2020.102629
Bandara et al.	2020	Privacy in e-commerce	Provides taxonomy of privacy concerns relevant to trust.	10.1007/s12525-019-00375-6

7. Research hypotheses

H1: AI personalization has a positive effect on customer experience.

H2: AI personalization has a positive effect on customer trust.

H3: Customer experience has a positive effect on customer trust.

H4: Customer experience has a positive effect on customer loyalty.

H5: Customer trust has a positive effect on customer loyalty.

H6: AI personalization has a positive direct effect on customer loyalty.

H7: Customer experience mediates the relationship between AI personalization and customer loyalty.

H8: Trust mediates the relationship between AI personalization and customer loyalty.

H9: Customer experience and trust form a sequential mediation path between AI personalization and customer loyalty.

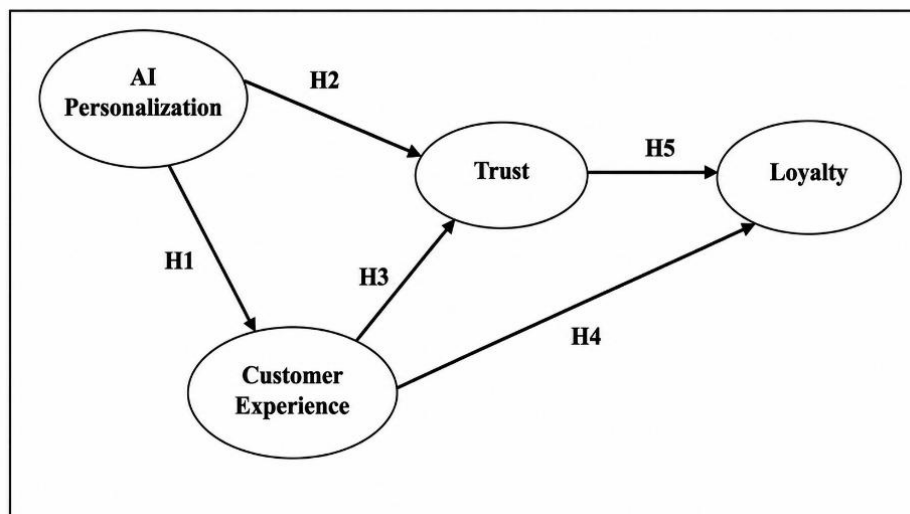


Figure 1. Proposed conceptual model of intelligent CRM in the platform economy

Methodology

1. Research philosophy and design

The proposed study adopts a positivist philosophy and a deductive, quantitative research design. The objective is to test theoretically derived relationships among latent constructs rather than to generate theory inductively. A cross-sectional survey is appropriate because the model concerns customers' current perceptions of AI personalization, their recent platform experience, trust, and loyalty intentions. The unit of analysis is the individual customer who actively uses a digital platform that employs data-driven recommendations or automated service features.

2. Study context and population

The target population consists of adult users of digital platforms, including e-commerce marketplaces, food-delivery applications, mobility platforms, online travel services, subscription-based digital services, and related app-based ecosystems. Respondents should have used at least one platform during the preceding three months and should have encountered a personalized recommendation, tailored offer, automated support feature, or algorithmically curated interface. Screening questions should be included before the main survey so that respondents without relevant exposure are excluded.

3. Sampling strategy and sample size

A purposive screening approach combined with convenience or panel-based recruitment can be used to reach qualified platform users. For PLS-SEM, the final sample should be sufficiently large to estimate the structural paths and mediation effects with acceptable statistical power. Rather than relying only on the traditional "10-times rule," the study should conduct an a priori power analysis based on the maximum number of predictors for the most complex endogenous construct, the minimum effect size of interest, $\alpha = .05$, and desired power of at least .80. A practical target of approximately 350-450 usable responses is recommended to permit robust measurement assessment, bootstrapping, subgroup diagnostics, and data-quality screening.

4. Questionnaire design

The questionnaire should contain four parts: screening questions, construct measures, platform-use characteristics, and respondent demographics. Construct items should be adapted from established pre-2021 literature and reworded only where necessary to fit AI-enabled platform services. Responses can be captured using a five-point or seven-point Likert scale anchored from strongly disagree to strongly agree. To reduce common method bias, the questionnaire should use concise wording, psychologically separate predictor and outcome sections, vary item order where practical, assure anonymity, and avoid implying preferred answers.

5. Operationalization of constructs

Table 2: Conceptualization, Measurement Dimensions, and Roles of Study Constructs

Construct	Conceptual meaning	Indicative dimensions/items	Primary literature base	Expected role
AI personalization	Perceived extent to which AI tailors' content and service to the individual.	Relevance, tailored recommendations, preference fit, adaptive offers, individualized support.	Aguirre et al. (2015); Davenport et al. (2020)	Exogenous predictor
Customer experience	Overall evaluation of interactions across the platform journey.	Ease, usefulness, informativeness, enjoyment, consistency, convenience.	Rose et al. (2012); Lemon & Verhoef (2016); Bleier et al. (2019)	Mediator / endogenous
Trust	Willingness to rely on the platform under uncertainty.	Competence, reliability, integrity, benevolence, data confidence.	Gefen et al. (2003); Sirdeshmukh et al. (2002); Martin & Murphy (2017)	Mediator / endogenous

Customer loyalty	Intention to maintain and deepen the platform relationship.	Reuse, repurchase, preference, recommendation, resistance to switching.	Srinivasan et al. (2002); Sirdeshmukh et al. (2002)	Final endogenous outcome
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6. Pilot testing and content validity

Before full deployment, the instrument should be reviewed by at least three subject experts in marketing, CRM, digital business, or information systems to assess content relevance and wording clarity. A pilot test with approximately 30-50 qualified platform users should then evaluate completion time, item comprehension, response variability, and preliminary reliability. Items that are ambiguous, redundant, or consistently misunderstood should be revised before the main survey. If the study is conducted in more than one language, translation and back-translation procedures should be used.

7. Data collection procedure and ethics

Data collection should be conducted through a secure online survey. Participants should receive a short information statement explaining the research purpose, voluntary participation, approximate completion time, anonymity, and data-handling procedure. No unnecessary personally identifying information should be collected. Respondents should provide informed consent before accessing the questionnaire. Duplicate responses, unrealistically short completion times, straight-lining, and failed attention checks should be screened according to predetermined criteria rather than removed opportunistically after seeing the results.

8. Data analysis strategy

PLS-SEM is recommended because the framework contains multiple latent variables, direct and indirect effects, and a prediction-oriented objective. Analysis can be conducted using SmartPLS or an equivalent SEM package. The procedure should proceed in stages. First, data screening should assess missing values, unengaged responses, outliers, and descriptive distributions. Second, the reflective measurement model should be evaluated using indicator loadings, internal consistency reliability, convergent validity, and discriminant validity. Cronbach's alpha and composite reliability values of approximately .70 or higher are generally desirable; average variance extracted (AVE) should be at least .50; and

discriminant validity should be assessed using the heterotrait-monotrait ratio (HTMT) together with cross-loading diagnostics where appropriate. Third, the structural model should be assessed for collinearity, path coefficients, significance using bootstrapping, coefficients of determination (R^2), effect sizes (f^2), and predictive relevance or out-of-sample predictive performance. Finally, indirect effects should be examined to test H7-H9. Mediation conclusions should rely on bootstrapped confidence intervals rather than the significance of individual component paths alone.

9. Common method bias and robustness checks

Procedural and statistical remedies should be used to address common method bias. Procedurally, predictor and criterion variables should be separated in the survey and respondent anonymity emphasized. Statistically, full-collinearity variance inflation factors, marker-variable procedures where feasible, or a common latent factor sensitivity analysis can be used as supplementary diagnostics. Robustness checks may also compare high- versus low-frequency platform users, different platform categories, or respondents with different levels of AI familiarity. These checks should be treated as secondary unless specified a priori.

10. Proposed Analytical Model and Decision Rules

The structural model contains AI personalization as the principal exogenous construct, customer experience and trust as intermediate endogenous constructs, and customer loyalty as the final outcome. H1-H6 test direct effects. H7-H9 test indirect effects. A positive path is considered supported only when its bootstrapped confidence interval excludes zero in the hypothesized direction. The magnitude of the coefficient, practical effect size, explained variance, and predictive performance should be interpreted alongside statistical significance. This prevents the study from treating very small but statistically significant effects as automatically managerially meaningful.

Table 3: Proposed Hypotheses, Structural Paths, and Decision Criteria

Hypothesis	Path	Expected direction	Decision criterion
H1	AI personalization → Customer experience	Positive	Bootstrapped CI excludes 0
H2	AI personalization → Trust	Positive	Bootstrapped CI excludes 0
H3	Customer experience → Trust	Positive	Bootstrapped CI excludes 0
H4	Customer experience → Loyalty	Positive	Bootstrapped CI excludes 0
H5	Trust → Loyalty	Positive	Bootstrapped CI excludes 0
H6	AI personalization → Loyalty	Positive	Bootstrapped CI excludes 0
H7	AI personalization → Experience → Loyalty	Positive indirect	Indirect-effect CI excludes 0
H8	AI personalization → Trust → Loyalty	Positive indirect	Indirect-effect CI excludes 0
H9	AI personalization → Experience → Trust → Loyalty	Positive sequential indirect	Indirect-effect CI excludes 0

Results

Because no primary dataset was provided for this methodology paper, empirical coefficients are intentionally not invented. The results expected from the theoretical model are reported as directional propositions and a publication-ready reporting structure. Based on prior research, AI personalization is expected to have its strongest relational effect when customers experience the personalization as useful and relevant rather than intrusive. This expectation is consistent with Aguirre et al. (2015), who show that personalization responses depend on information-collection conditions, and with Davenport et al. (2020), who identify personalization as a major application of AI while warning about privacy and ethical risks.

Customer experience is expected to emerge as a substantial mediator because algorithmic capabilities have little relational value unless they improve the customer's journey. Lemon and Verhoef (2016) stress that experience accumulates across touchpoints, while Rose et al. (2012) and Bleier et al. (2019) demonstrate that online design and interaction characteristics shape customer evaluations and subsequent behavior. In the present model, personalization should therefore improve loyalty partly by making platform interactions more relevant, convenient, informative, and engaging.

Trust is also expected to be a decisive mechanism. Gefen et al. (2003) show that trust is central in online shopping, and Sirdeshmukh et al. (2002) link trust to value and loyalty. In an AI-enabled platform context, trust is likely to capture not only confidence in the firm but also confidence in automated decisions, data practices, and service reliability. If personalization is perceived as invasive or opaque, the positive effect of relevance may be weakened. The privacy literature (Martin & Murphy, 2017; Bandara et al., 2020) therefore suggests that trust should be interpreted as both a relational asset and a governance outcome.

The direct path from AI personalization to loyalty may remain significant after including experience and trust, but theory suggests that part of the effect should be transmitted through these mediators. A finding of partial mediation would indicate that personalization creates loyalty through both experiential-relational mechanisms and additional benefits such as reduced search cost or improved product matching. A finding of full mediation would suggest that personalization by itself is insufficient: customers become loyal only when the technology creates a positive experience and earns trust. Either pattern would be theoretically meaningful and should be interpreted using effect sizes and confidence intervals rather than significance alone.

Results reporting table

Table 4: Structural Model Path Coefficients and Hypothesis Testing Results

Path	β	SE	t	p	95% CI	Decision
AI personalization → Customer experience	To report	To report	To report	To report	To report	Supported / Not supported

AI personalization → Trust	To report	To report	To report	To report	To report	Supported / Not supported
Customer experience → Trust	To report	To report	To report	To report	To report	Supported / Not supported
Customer experience → Loyalty	To report	To report	To report	To report	To report	Supported / Not supported
Trust → Loyalty	To report	To report	To report	To report	To report	Supported / Not supported
AI personalization → Loyalty	To report	To report	To report	To report	To report	Supported / Not supported
Indirect: AI personalization → Experience → Loyalty	To report	To report	To report	To report	To report	Supported / Not supported
Indirect: AI personalization → Trust → Loyalty	To report	To report	To report	To report	To report	Supported / Not supported
Sequential indirect: AI personalization → Experience → Trust → Loyalty	To report	To report	To report	To report	To report	Supported / Not supported

Measurement-model reporting checklist

A final empirical paper should report indicator loadings, Cronbach's alpha, composite reliability, AVE, and HTMT values for every construct. Items with weak loadings should not be deleted mechanically; deletion must be justified by both statistical performance and construct content. The paper should also report collinearity diagnostics, R^2 values for customer experience, trust, and loyalty, f^2 effect sizes for major paths, and a predictive assessment. These statistics will show whether the model is merely statistically significant or genuinely useful for explaining and predicting customer loyalty in the platform economy.

Conclusion and Discussion

This methodology paper reconceptualizes customer relationship management for the platform economy by positioning AI personalization as a relational capability rather than a stand-alone technological feature. The proposed framework integrates four constructs that are frequently studied separately: AI personalization, customer experience, trust, and loyalty. The central argument is that intelligent CRM succeeds when algorithms improve the customer journey and strengthen confidence in the platform. Personalization may create relevance and convenience, but these benefits do not automatically become loyalty. Customers interpret personalization through the quality of their experience and through beliefs about the platform's reliability, integrity, and handling of personal data. The framework extends strategic CRM thinking by adapting the integrated logic of Payne and Frow (2005) to data-rich platform settings. It also incorporates the platform

perspective of de Reuver et al. (2018) and McIntyre and Srinivasan (2017), which emphasizes that interactions occur within ecosystems characterized by network effects and digital architectures. AI research further explains how analytical and service tasks can be automated or augmented (Huang & Rust, 2018; Davenport et al., 2020). The resulting iCRM perspective is therefore both technological and relational: the platform uses AI to interpret data, but customer outcomes depend on how these algorithmic decisions are experienced and trusted. A key theoretical contribution is the explicit placement of customer experience and trust between AI personalization and loyalty. The customer-experience literature shows that value is created across journeys and touchpoints rather than at a single transaction (Lemon & Verhoef, 2016). Online experience research further demonstrates that design characteristics influence customer responses (Rose et al., 2012; Bleier et al., 2019). Trust research shows why customers must be willing to rely on a digital provider when uncertainty exists (Gefen et al., 2003), while loyalty research demonstrates that relational quality and customized interaction are important for continued patronage (Sirdeshmukh et al., 2002; Srinivasan et al., 2002). Combining these perspectives provides a more complete explanation than a simple direct AI-to-loyalty model. The personalization-privacy tension is equally important. Aguirre et al. (2015) demonstrate that personalization effectiveness is contingent on information-collection practices, and Martin and Murphy (2017) argue that privacy is fundamental to responsible marketing. Bandara et al. (2020) further show that e-commerce privacy concerns span multiple themes. These findings imply that a technically accurate recommendation can still damage

relationships if customers view the underlying data use as opaque, excessive, or unfair. Platform managers should therefore treat transparency, explainability, permission, and security as components of customer experience and trust rather than as separate compliance activities. Managerially, the proposed model suggests four priorities. First, AI personalization should focus on customer-relevant utility rather than maximum possible targeting. Second, personalization should be orchestrated across the entire journey so that recommendations, service messages, and automated support remain consistent. Third, platform firms should actively design for trust through reliable service performance, responsible data practices, understandable privacy choices, and appropriate human support when automated systems fail. Fourth, loyalty metrics should be connected to experience and trust measures so that managers can distinguish short-term response to a recommendation from durable relationship quality. The proposed research design has limitations that future empirical work should address. A cross-sectional survey cannot establish temporal causality as strongly as longitudinal or experimental designs. Self-reported perceptions may also differ from observed platform behavior. Future studies could combine survey measures with clickstream, transaction, or recommendation-exposure data; test the model across different platform categories; compare algorithmic and human-assisted service; or examine whether privacy concern, AI familiarity, perceived control, or platform switching costs moderate the relationships. Cross-cultural comparisons would also be valuable because norms regarding personalization, trust, and data use vary across markets. In conclusion, intelligent CRM in the platform economy should be evaluated as a relational system in which AI personalization shapes experience, experience shapes trust, and trust contributes to loyalty. The methodological framework presented here offers a transparent way to test these relationships without fabricating outcomes. Its empirical implementation can help researchers and managers determine not merely whether AI personalization works, but how, through which relational mechanisms, and under what conditions it produces sustainable customer loyalty.

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