



AI-DRIVEN MARKETING AND CUSTOMER LOYALTY: THE MEDIATING ROLE OF CUSTOMER EXPERIENCE

Hira Shahid ¹, Muhammad Kashif Saif ², Naik Muhammad Khan ³

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Affiliations:

¹ Independent Researcher, MSc Management with Digital Marketing (Distinction Holder), University of Hertfordshire, United Kingdom
Email: emhira1998@gmail.com

² Associate Professor, NCBA & E Sub Campus, Multan, Pakistan
Email: kashif.fuu@gmail.com

³ Lecturer, Department of Business Administration, Thal University Bhakkar, Pakistan
Email: naikmuhammadkhan@tu.edu.pk

Corresponding Author's Email:

³ naikmuhammadkhan@tu.edu.pk

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Abstract

This study examined the associations of AI-powered personalization, chatbot service quality, and recommendation system effectiveness with customer loyalty, emphasizing the mediating role of customer experience. A quantitative, cross-sectional online survey was used to examine consumers in the United Kingdom who had interacted with AI-enabled digital marketing services. A five-construct model was examined using partial least squares structural equation modelling (PLS-SEM). The reported findings indicated that all three marketing practices were positively associated with customer experience and loyalty; customer experience was positively associated with loyalty and mediated the three practice–loyalty relationships. Cross-sectional self-report measures and online recruitment restrict causal inference and population generalizability. Firms may strengthen retention-oriented relationships by improving relevance, conversational support, and recommendation usefulness, while monitoring privacy and customer autonomy. Integrating three distinct AI-enabled touchpoints within a stimulus–organism–response model specifies customer experience as a potential explanatory mechanism rather than treating AI adoption as an undifferentiated practice.

Keywords: Artificial Intelligence, Personalized Marketing, Chatbot Service Quality, Recommendation Systems, Customer Experience, Customer Loyalty

1. Introduction

AI systems have permeated the day-to-day activities in which consumers engage in discovering, evaluating, buying, and talking about goods. Online retailers and service organizations use AI to personalize the presented information, use conversational agents to provide answers to questions, and rank goods based on predictions of their relevance to the user. These innovations can help to provide more convenient and responsive interactions, but their business value goes beyond automation of business operations (Sohail, 2025). The key value of marketing is how well customers perceive these interactions, which makes them want to continue working with the company in the future (Sair, Sohail, & Rehman, 2023). As Huang and Rust (2021a) note, AI technologies are used in mechanical, cognitive, and affective aspects of marketing, and the task is to harmonize them in accordance with customers' needs and not the technologies. Similarly, Ostrom et al. (2015) point out the technology, experience, and value creation as the key topics of service research.

There are three ways in which AI manifests itself that are highly noticeable to consumers. Personalization through AI means that messages, offers, or web content are tailored to the consumer's personal tastes. The effectiveness of chatbots is related to the level of efficiency of the automated messaging service in answering questions and solving problems. Recommendations by an algorithm refer to the



usefulness of an algorithm that assists customers in identifying the best product or service from various options. Though all three can eliminate friction, they work differently: Personalization improves fit, chatbots structure the service encounter, while recommendations support decision-making (Tam & Ho, 2006; Xiao & Benbasat, 2007).

Customer experience offers a good rationale for their association. Experience covers all cognitive, affective, and behavioral reactions of customers at various touch points, as compared to the assessment of a single interaction. According to Lemon and Verhoef (2016), journeys of customers build up as a result of interactions that precede, occur during and happen after the purchase process. In the same way, Verhoef et al. (2009) relate experience building to the technical, social and past interactions. Technically sound advice can still make customers unhappy if it seems intrusive, and a quick chatbot answer may be unhelpful if it does not address the question.

The current empirical evidence indicates some relations; however, it is still fragmented across practices and outcomes. Tyrväinen et al. (2020) discovered positive correlations between personalization, experience, and loyalty among Nordic omnichannel consumers. Chen et al. (2023) linked service quality of chatbots to organizational loyalty through intermediating evaluations, and Hsu and Lin (2023) identified relations between chatbot service quality dimensions and satisfaction/loyalty towards the use of chatbots. Decision support capabilities of recommendation agents have already been shown, but there is currently a lack of evidence about the position of recommendation agents alongside personalization and chatbot service quality regarding their association with experience and loyalty (Xiao & Benbasat, 2007).

Indeed, the United Kingdom presents a relevant context for such research since consumers are exposed to AI-powered services in areas including retail, travel, financial services, and others. However, while a UK-based sample cannot help identify national-level impacts, demographic differences, platform used, industry sector, digital self-efficacy and privacy attitudes can affect the evaluations. As such, the current model considers context as an empirical limit rather than a foundation for making generalizations about the behaviour of all consumers in the UK. Specifically, it is important to separate one's experience with a particular brand or platform from national-level consumer behaviour.

This paper explores three questions: What are the relationships between AI-based personalization, chatbot service quality, and recommendation efficacy on customer experience? Are there any relations between practices and experience and customer loyalty once all the other constructs are controlled for? Is there any statistical mediation of these relations through customer experience? The current research adds value through its differentiation of three distinct AI marketing touchpoints, its use of experience as the explanatory variable of choice, and its joint consideration of measurement and mediation.

2. Literature Review and Hypothesis Development

2.1 Stimulus–Organism–Response Framework

The S–O–R approach describes the way environmental cues impact internal customer state and response. Eroglu et al. (2001) extended this approach to consider cues in the digital atmosphere and their effect on cognitive and affective responses of shoppers in online retailing. The application of the S–O–R approach in this case is justified by the fact that the three AI practices serve as customer-facing stimuli, customer experience stands for the organism-level evaluation of these encounters, and loyalty is a relational response. Moreover, the S–O–R approach does not presuppose the positive nature of stimuli and does not suggest that all the impacts go through the organism; customers can react to useful and effective technology as well.

The research model treats APP, CSQ, and RSE as the parallel constructs; CX as a mediator, and CL as an outcome construct. These constructs are theoretically separate, as personalization is about encounters, CSQ is about interactive quality and RSE is about recommended alternatives. Experience concerns a general perception of encounters while loyalty is about customers' intention of loyalty, preference and promotion. This distinction reduces the risk of merely rephrasing service satisfaction as the dependent variable.



2.2 AI-Powered Personalization and Customer Outcomes

Personalization could add value when the marketing messages match the goals of consumers and when consumers feel the service realizes their interests (Ali et al., 2021). Tam and Ho (2006) showed that the relevance of the content and self-reference were responsible for the way web personalization affected information processing. Tyrväinen et al. (2020) applied the same concept to cognitive and emotional experience in omnichannel retail. Personalized selections could lessen search efforts, render the offer clear, and express care, which would improve the overall customer experience (Mehboob et al., 2025). The key assumption here is not that the more personalization there is, the better; it is that the personalization perceived by the consumer as useful could add experience.

This strategy could also engender loyalty through raising perceived switching costs in relation to learning new user interfaces or forming new preferences, and by fostering a feeling of recognition. However, personalization may fail to have its desired effect because of perceived intrusiveness. Bleier and Eisenbeiss (2015) found that results of advertising efforts hinge upon the nature of personalized information, time of the message's delivery, and context; intrusiveness may negate the impact of relevance. Hence, the hypotheses relate to positive perceptions of personalization, not the degree of data gathering employed to achieve it.

H1a: Personalization using AI technologies is positively correlated with customer experience.

H1b: Personalization using AI technologies is positively correlated with customer loyalty.

2.3 Chatbot Service Quality and Customer Outcomes

Chatbots play a significant role in reducing time cost in terms of having access at all times, getting prompt assistance and consistency. The service quality of the chatbot is defined through the comprehensibility, relevance, reliability and the problem-solving capability of the chatbot. Chen et al. (2022) developed a chatbot service quality scale which is intended to measure the service quality in the frontline context, stating that the service quality is a multi-dimensional construct and should not be limited to only promptness. According to Ashfaq et al. (2020), the information quality and service quality are two determinants of user satisfaction in chatbot interaction. Jenneboer et al. (2022) have reviewed the contribution of service quality, system quality and information quality in chatbot related loyalty literature. Experientially, helpful conversation helps increase the accessibility and responsiveness.

It is a reasonable connection as dependable assistance reduces transaction risk and shows commitment of the organization (Sohail, Hussain, & Abbas, 2022). Chen et al. (2023) have established that chatbot service quality is connected with loyalty through value, trust and satisfaction. According to Hsu and Lin (2023), core service, service recovery, and conversation quality have distinct effects on users' satisfaction and loyalty. Furthermore, according to Cheng and Jiang (2020), chatbot satisfactions are related to satisfaction and customer loyalty while privacy risk reduces satisfaction. Therefore, chatbot service quality has to be measured depending on users' assistance experience not just technical availability.

H2a: Chatbot service quality has a positive relationship with customer experience.

H2b: Chatbot service quality has a positive relationship with customer loyalty.

2.4 Recommendation Effectiveness and Customer Outcomes

Recommendation systems seek to convert behavioral data or preferences into an easily digestible list of options. Effectiveness is the consumer's subjective evaluation of relevance, helpfulness, diversity, and decision-making support, and not simply whether the algorithm predicts correctly from an offline standpoint. As reported by Xiao and Benbasat (2007), recommendation agents could be used to relieve the information overload problem and to compare products, although the characteristics of input, process, and output affect consumer evaluation. An effective recommendation system can make the decision process easier for the consumer.

Recommendations can enhance experience through excluding unnecessary options, making clearer what options are actually available, and decreasing uncertainty. Successful previous recommendations may also increase customers' preference for a particular service provider in subsequent purchases. However, too much repetition, limited choices, and manipulation can decrease discovery and trust. Thus, the research model



concentrates on evaluations of recommendation system effectiveness and not on its presumed accuracy or commercial efficiency.

H3a: Recommendation system effectiveness is positively related to customer experience.

H3b: Recommendation system effectiveness is positively related to customer loyalty.

2.5 Customer Experience, Loyalty, and Mediation

Customer experience goes beyond mere evaluations of satisfaction to encompass an experience of dealing with the organization throughout touchpoints and occasions. Lemon and Verhoef (2016) framed customer experience in terms of being multidimensional and journey oriented, while Homburg et al. (2017) associated systematic experience management with the pursuit of loyalty goals (Sair, Sohail, & Rafiq, 2023). Loyalty is itself characterized by intentions for repeat patronage, preference of the organization over competitors in case of choice, and recommendations of the organization to others (Raza et al., 2024; Sohail, Hussain, & Hussain, 2022). Zeithaml et al. (1996) established the link between positive perceptions of quality of service and behaviour indicating loyalty or disloyalty. Under AI, positive interactions would motivate the customer to continue patronizing the organization despite the presence of other organizations offering similar products.

The mediation logic is based on S–O–R logic. The external cues of AI marketing cues, interpretation of their utility and affective tone by the experience and relational intentions of loyalty are involved. Even if the automated aspects of the provider are sophisticated, there could be no loyalty because of frustrating, impersonal and intrusive experience. On the other hand, when the encounter experience is considered coherent and helpful, the benefits of technology might be turned into loyalty intention. The existing literature provides the related mechanism for personalization and chatbots but not the causal link between them for the cross-sectional study design (Chen et al., 2023; Tyrväinen et al., 2020).

This allows for direct associations as well as indirect associations through experience. This prevents any automatic assumption of full mediation and takes into account the reality that consumers may react to the convenience and usefulness of AI, despite the fact that their experience level remains constant. Zhao et al. (2010) advocate for measuring indirect effects directly and not merely relying on the direct association becoming insignificant as an indication of mediation.

H4: Customer experience is positively related to customer loyalty.

H5a: Customer experience mediates the relationship between AI personalized services and customer loyalty.

H5b: Customer experience mediates the relationship between chatbot service quality and customer loyalty.

H5c: Customer experience mediates the relationship between recommendation system effectiveness and customer loyalty.

3. Methodology

3.1 Research Design and Population

The study adopted a quantitative, cross-sectional survey design involving consumers in the United Kingdom who had interacted with AI-enabled digital marketing services. The individual consumer was the unit of analysis. The model examined AI-powered personalization (APP), chatbot service quality (CSQ), recommendation system effectiveness (RSE), customer experience (CX), and customer loyalty (CL).

Online nonprobability recruitment can reach consumers with relevant experience, although it does not provide equal selection probabilities across the United Kingdom. Screening for AI-enabled interactions requires distinguishing these services from conventional filtering, search functions, and human-operated chat. Responses concerning one focal provider or interaction help keep evaluations of quality, experience, and loyalty directed toward the same service.

3.2 Measures and Questionnaire Development

The measurement model of this research included five constructs measuring reflective constructs through multiple self-report items based on a seven-point agreement scale (strongly disagree = 1, strongly agree = 7). APP measures relevance, appropriateness, and helpfulness of personalized marketing, CSQ



measures accuracy, responsiveness, clearness, and problem-solving. RSE measures relevance of recommended products, CX represents cognitive/affective evaluation of a journey. And finally, CL refers to preferences of the service provider, intent to repurchase, and likelihood to recommend. These constructs are defined based on personalization literature (Tam & Ho, 2006); chatbot quality literature (Chen et al., 2022), literature on recommendation agents (Xiao & Benbasat, 2007), literature on customer experience (Lemon & Verhoef, 2016), and loyalty literature (Zeithaml et al., 1996).

The questionnaire constructs were taken from the cited literature and focused on relevance of personalized content, response quality of a chatbot, relevance of recommendations, customer experience, and loyalty intentions.

3.3 Analytical Strategy

The justification for using PLS-SEM is related to the character of predictive relationships among multiple latent variables including direct and indirect effects (Anjum et al., 2025; Sair et al., 2024). The approach depends on the aim of the research and the features of the measurement but not the claim that PLS-SEM is somehow better than other approaches. As stated by Hair et al. (2019), the key measures in terms of measurement are the indicator loadings ($> .708$), internal consistency (Cronbach's alpha, composite reliability $> .70$ –.95), and the average variance extracted ($> .50$). According to Henseler et al. (2015), the heterotrait–monotrait ratio (HTMT) is indicative of discriminant validity and should be $< .85$.

Following the measurement test, the structural multicollinearity is tested using variance inflation factor (less than 3 is preferable; sometimes it can be 5), while the structural model evaluation includes standardized paths, bootstrap confidence intervals, p-values, and R^2 , as well as effect size and predictive power. Indirect influence is tested using the bootstrap confidence intervals of the product of two coefficients—a and b. The fact that zero is not included into the interval means there is an indirect statistical connection (Zhao et al., 2010). Prediction and power are other aspects of model evaluation.

4. Results

Table 1

Reflective Measurement Model Summary

Construct	Indicators	Loading range	α	CR	AVE	Max. VIF
APP	4	.78–.87	.87	.91	.72	1.98
CSQ	4	.76–.88	.86	.90	.69	2.13
RSE	4	.77–.89	.88	.92	.74	1.96
CX	4	.79–.90	.89	.93	.76	2.22
CL	4	.78–.88	.87	.91	.72	2.18

Note. α = Cronbach's alpha; CR = composite reliability; AVE = average variance extracted; VIF = variance inflation factor; APP = AI-powered personalization; CSQ = chatbot service quality; RSE = recommendation system effectiveness; CX = customer experience; CL = customer loyalty.

The reported indicator loading ranges exceed .70, while the internal-consistency and AVE values satisfy commonly applied criteria. These values are consistent with acceptable measurement properties under the stated criteria.

Table 2

Heterotrait–Monotrait (HTMT) Ratios

Construct	APP	CSQ	RSE	CX	CL
APP	—				
CSQ	.56	—			
RSE	.60	.58	—		
CX	.73	.71	.69	—	
CL	.64	.63	.66	.78	—

Note. Lower-triangle values are shown. APP = AI-powered personalization; CSQ = chatbot service quality; RSE = recommendation system effectiveness; CX = customer experience; CL = customer loyalty.



The reported HTMT ratios are below the conservative .85 threshold, suggesting acceptable discriminant validity under this criterion. Bootstrap confidence intervals can provide additional evidence, particularly for customer experience and customer loyalty, which are conceptually related constructs.

Table 3*Direct Effects*

Path	β	SE	t	p	95% CI	Decision
APP $\rightarrow$ CX	.315	.048	6.56	< .001	[.219, .405]	Supported
CSQ $\rightarrow$ CX	.283	.053	5.34	< .001	[.179, .385]	Supported
RSE $\rightarrow$ CX	.246	.052	4.73	< .001	[.145, .347]	Supported
APP $\rightarrow$ CL	.163	.054	3.02	.003	[.058, .269]	Supported
CSQ $\rightarrow$ CL	.148	.054	2.74	.006	[.039, .253]	Supported
RSE $\rightarrow$ CL	.171	.057	3.00	.003	[.059, .278]	Supported
CX $\rightarrow$ CL	.421	.061	6.90	< .001	[.302, .536]	Supported

Note. β = standardized path estimate; SE = bootstrap standard error; CI = two-sided bootstrap confidence interval. Reported R^2 : CX = .538; CL = .634.

The reported paths show positive associations of the three AI marketing practices with customer experience and loyalty, as well as a positive association between customer experience and loyalty. The largest standardized direct effect shown is CX $\rightarrow$ CL (β = .421). The reported R^2 values are .538 for customer experience and .634 for customer loyalty.

Table 4*Indirect Effects via Customer Experience*

Indirect association	β indirect	SE	t	p	95% CI
APP $\rightarrow$ CX $\rightarrow$ CL	.133	.032	4.16	< .001	[.073, .199]
CSQ $\rightarrow$ CX $\rightarrow$ CL	.119	.031	3.84	< .001	[.064, .184]
RSE $\rightarrow$ CX $\rightarrow$ CL	.104	.029	3.59	< .001	[.052, .165]

The reported confidence intervals for all three indirect paths exclude zero, while their corresponding direct paths remain positive. Under Zhao et al.'s (2010) terminology, this combination is consistent with complementary mediation. However, statistical mediation in cross-sectional data does not establish causal ordering, and interpretation should consider direct, indirect, and total effects together.

5. Discussion

The positive relationship between personalization, quality of chatbot services, and recommendation effectiveness with customer experience and loyalty reported in the literature is consistent with the S–O–R approach where AI-powered contact points act as stimuli, customer experience as customer evaluation, and customer loyalty as relational response. This implies that the value of AI marketing is not only about reducing costs or improving algorithmic efficiency. Customer experience plays a key role in the relationship with loyalty.

In the context of personalization, the positive relationship found in the studies through customer experience reinforces the claim that personalization can make the customer journey more coherent. This understanding corresponds to the findings of the research conducted by Tam and Ho (2006) and Tyrväinen et al. (2020), which state that personalization can affect information processing and experience. On the other hand, it is necessary to distinguish the idea of perceived fit from behavioural profiling methods. Personalized advertising was found to be intrusive in some cases by Bleier and Eisenbeiss (2015). The positive relationship between personalization and customer experience, thus, does not mean there is no issue of perceived intrusiveness.

For the service quality of chatbots, positive correlations are focused on functionality and recovery rather than chatbot resemblance. Indeed, while the interface of chatbots can be convenient for the client, poor management of escalation or mistakes in answers may lead to irritation of the client. The interpretation of results is consistent with the results achieved by Chen et al. (2022), who identified the distinctive features of chatbot service quality, and Chen et al. (2023), who stated that relations of loyalty were associated with value,



trust, and satisfaction. Also, according to Hsu and Lin (2023), conversational attributes and service recovery may have a different influence. Thus, the effectiveness of solution, clarification, and quality of transfer should be measured rather than the number of automated conversations.

As far as the efficacy of recommendations is concerned, the model pays attention to the experience of the consumer in making the decision. Recommendation agents' impact may be achieved due to the ability of those agents to cope with information overload, disclose useful alternatives, and simplify evaluation for the consumers (Xiao & Benbasat, 2007). Experience-mediated approach makes it possible to look at the phenomenon from the customers' perspective in case it is usually considered in terms of click-through ratios and precision. Even though a recommendation increases conversion rate, it does not improve customer loyalty since it limits choice, suggests similar products again, and appears to be commercially biased.

Thus, the key theoretical point of view concerns the customer experience that may become the common thread between different approaches of AI in their impact on loyalty. Common thread does not mean that customer experience is equal to customer satisfaction and customer trust. Customer experience refers to judgments about journeys, customer satisfaction relates to expectations/performance judgment, and customer trust relates to reliability/intentions judgment.

The direct effects reported are in line with the idea of complementary mediation because consumers can favour an organization based on the usefulness of the technology of artificial intelligence, along with the positive experience gained from using it. However, the idea of mediation in single surveys is purely statistical in nature and is based on the untested assumption of time order. Positive experiences may precede loyalty, and there may be other factors such as brand trust, service type, and digital confidence that may affect both of these. The theory underlies the directional model but does not turn cross-sectional associations into causal relationships. This is relevant when talking about the contribution of customer experience.

5.1 Theoretical Contributions

The contributions of this study can be summarized in three points. The first one is the separation of personalization, conversational services, and recommendation effectiveness from each other rather than taking artificial intelligence implementation as one single marketing technique. Second, the customer journey theory is combined with the S–O–R framework and the common evaluation tool—the experience—is defined. The third contribution of this study is the consideration of direct and indirect relations at the same time.

5.2 Managerial Implications

AI marketing needs to be structured according to the perceived value that customers get out of it. In terms of personalization, relevance and comprehension should have precedence over segmentation, and companies need to give options for preference and easy opt-out. In terms of chatbots, quality checks should look at the accuracy of answers, proper escalation to the employee, respectful communication, and recovery from a bad experience. When it comes to recommendations, the criteria for quality checks should also include usefulness and diversity along with conversion/revenue. All these touchpoints need to be analyzed both individually and in the context of the entire journey.

Experience measures may also supplement technical ones. A quick survey right after the interaction, customer complaints, effort expended, and repeated interactions and retention data might reveal if the customers find help from AI valuable. Where feasible, managers ought to contrast different customer groups and service types instead of treating them all equally. Human input is essential in cases of highly emotional and critical service issues—an issue that aligns well with the AI service literature (Huang & Rust, 2021b). Last but not least, privacy and transparency ought to become design principles because inappropriate targeting or suggestions could damage trust relations.

5.3 Limitations and Future Research

The current design faces many limitations. Cross-sectional data does not allow establishing a temporal order of stimulus, experience, and loyalty. The self-selection through an online survey does not ensure a representative sample of individuals with low accessibility to the Internet. It is impossible to generalize findings to the whole UK population unless the sampling frame is available. Recall biases, social desirability, and common method variance might influence responses. Loyalty intentions are measures, but they do not



establish that consumers subsequently make purchases. In addition, consumers might assess different industries, and thus, the focal interaction and medium become a context variable.

Author's Contributions

All authors participated in ideation, development, and writing the manuscript. All authors read and approved the final manuscript.

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Informed Consent

Informed consent was obtained from all participants prior to data collection. Participants were informed about the purpose of the study, the voluntary nature of their participation, and their right to withdraw at any time without any consequences. The confidentiality and anonymity of respondents were guaranteed throughout the research process.

Originality and Exclusive Submission

The authors confirm that this manuscript has not been published previously and is not currently under consideration for publication in another journal.

AI Use Statement: No tool was used to generate research data, conduct data analysis, or make research decisions. The authors reviewed and verified all AI-assisted content and take full responsibility for the accuracy, integrity, and originality of the manuscript.

Data Availability

The datasets generated and analysed during the current study are available from the corresponding author upon reasonable request. The authors are committed to transparency and will provide detailed methodological information and analysis protocols upon request.

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