THE INFLUENCE OF AI-DRIVEN MARKETING ON CUSTOMER ENGAGEMENT AND BRAND LOYALTY: A PLS-SEM ANALYSIS OF SMARTPHONE CONSUMERS IN ERBIL

Idrees HASAN
Salahaddin University - Erbil, Erbil, Iraq
idrees.hasan@su.edu.krd

Saman OTHMAN
Soran University, Erbil, Iraq
saman.othman@soran.edu.iq

Abstract
This research explores the relationships between aspects of AI powered marketing at chatbot interface, personalization, and recommendations and how they impact Xiaomi smartphone users' perceptions of customer engagement (cognitive, affective, and behavioral), and brand loyalty in the City of Erbil. This relationship has been evaluated using survey data from a heterogeneous sample of consumers utilizing Partial Least Squares Structural Equation Modeling PLS-SEM and found a good model fit. The analysis confirms the significant positive impact of AI powered marketing on customer engagement in each of its three dimensions. Additionally, all three dimensions of engagement were found to be positive significant predictors of brand loyalty with affective engagement being the dimension with the most significant direct effect. The analysis of total effects also reinforced previous research on the role of perceived personalization as a strong predictor of brand loyalty. The findings add to the growing body of research in digital marketing and consumer behavior as well as provide useful managerial recommendations to brand managers competing in the highly competitive, technology driven marketplace.
Keywords: Artificial Intelligence (AI), Marketing, Customer engagement, Loyalty, Xiaomi.
DOI: https://doi.org/10.24818/beman/2025.15.3-03

1. INTRODUCTION

1.1 Background and problem statement

The transformation of commerce in the digital age has dramatically affected the relationship of brands with their consumers. With the introduction of various artificial intelligence (ai) technologies, more marketing touchpoints are being utilized that are continuing to change the customer journey particularly in the consumer electronics industry. Brands such as Xiaomi that depend on selling large volumes and a strong

Business Excellence and Management
Volume 15 Issue 3 / September 2025

Business Excellence and Management
Volume 15 Issue 3 / September 2025

brand presence in multiple markets are increasingly using ai powered tools and technologies such as automated chatbots, personalized content distribution and ai driven recommenders or product suggestions to reach their customer base. While many of the ai tools and technologies being used today were once new and novel, truly understanding how these specific digital interactions result in the omni-channel and multi-faceted concept of customer engagement and ultimately long-term brand loyalty is an important area of research that remains.

This research aims to address this gap empirically by testing a structural model that maps the impact of ai marketing components to the various dimensions of customer engagement and finally to brand loyalty. The research is situated in the specific cultural and market context of erbil, which is a rapidly developing metropolitan area that has a cohort of consumers who are technologically engaged; thus, creating the opportunity to understand their composition. Analyzing a single brand, xiaomi, allows the study to control for brand-specific variables and facilitate a systematic analysis that has both theoretical rigor and practical insights.

The competition for smartphones in erbil is fluid and generally competitive, with Xiaomi being positioned against several notable international brands. the recent market data for Iraq indicates that Samsung has a clear leadership market share at 20.93% with apple in second with a share of 17.29%. Xiaomi is in a strong position at 9.65% alongside other major players such as infinix (11.86%), honor (9.81%), and tecno (9.48%) (statcounter global stats, 2025).

Although there are several competitors in the market and some competitors are overly expensive, brands like Xiaomi and Transsion (Infinix, Tecno) have grown to become accepted and trusted brands among Iraqi consumers as they are primarily focused on the budget segment (Pravinkumar & Chaurasia, 2023). Additionally, Xiaomi has proactively sustained excellent, physical engagement with consumers as they currently have over eight, physical stores across main cities, including Erbil. This can provide significant contributions to brand awareness and customer relationship development (Pravinkumar & Chaurasia, 2023).

1.2 Research objectives

The current research objectives include the following:

- To explore the direct impacts of perceived personalization, recommendations, and a chatbot experience on cognitive, affective, and behavioral customer engagement.
- To explore the direct effects of each dimension of customer engagement on brand loyalty.
- To explore the total effects of the AI-driven marketing components on brand loyalty.
- To provide data-based recommendations for increasing Xiaomi marketing activities within the Erbil market.

2. THEORETICAL FRAMEWORK AND LITERATURE REVIEW

2.1 AI-driven marketing and the customer journey

The theoretical foundation of this research is based on the growing reality that AI technologies are no longer just productivity tools, but they are part of the way organizations create a meaningful customer experience. The AI-enhanced marketing dimensions analyzed are the following:

Perceived Personalization: This is how consumers view a brand's marketing strategy aimed at them, which is based on their individual interests and needs, rather than a generic mass market approach (Kumar and Rajan, 2019; Huang and Rust, 2021). Perceived personalization is rooted in the one-to-one marketing concept. It is expected to create a stronger perceived connection with the customer by making them feel understood and valued (Huang and Rust, 2021).

Recommendations: AI-powered recommendations systems are designed to leverage user data to predict and recommend products, accessories, or features that a user may like (Li and Karahanna, 2015). Notably, the perceived relevance of recommendations serves a critical role because it can positively add to product discovery and perceived value (Pu et al., 2018; Smith et al., 2000).

Chatbot Experience: Automated chatbots can provide immediate customer support and information (Adam et al., 2021). Considered as a touchpoint to evaluate the brand's service quality, a good customer chatbot experience (e.g., being helpful and responsive), is influential in shaping customers' immediate perceptions (Adam et al., 2021; Hsu and Lin, 2023; Prentice et al., 2020).

2.2 A multidimensional approach to customer engagement

Customer engagement is a complicated, multi-dimensional construct that extends beyond satisfaction or purchase behaviors (Hollebeek et al., 2014; Vivek et al., 2014). This paper adopts a widely accepted framework that presents three dimensions of engagement (Brodie et al., 2011; Hollebeek et al., 2014):

Cognitive Engagement: This dimension reflects the mental and psychological amount of effort a consumer invests in a brand. It is measured by the amount of attention a consumer pays to brand news, cognition surrounding brand features and technology, and interest in learning more about a brand.

Affective Engagement: This dimension refers to the emotional attachment a consumer feels towards a brand and the positive emotions associated with it. It is seen in feelings of pride, strong association, or feeling part of a brand community.

Behavioral Engagement: This dimension represents the visible, physical actions taken by a consumer in relation to a brand. This includes recommending a brand to someone else, following a brand on social media, or participating in online brand activities.

Business Excellence and Management
Volume 15 Issue 3 / September 2025

2.3 Getting from engagement to loyalty

Brand loyalty, the ultimate measure of effectiveness for a brand, is recognized as a degree of commitment to repurchase a product or service (Reichheld and Teal, 2001). This study frames the three dimensions of customer engagement as the primary psychological and behavioral antecedents to loyalty. The survey instrument captures loyalty in two ways; a direct statement referring to the likelihood of future purchase and a Net Promoter Score type of question that captures attitudinal and behavioral loyalty dimensions.

2.4 Hypotheses development

Using the theory as a basis, the following hypotheses are offered to help structure the model.

H1a-c: Perceived Personalization, Recommendations, and Chatbot Experience positively influence Cognitive Engagement.

H2a-c: Perceived Personalization, Recommendations, and Chatbot Experience positively influence Affective Engagement.

H3a-c: Perceived Personalization, Recommendations, and Chatbot Experience positively influence Behavioral Engagement.

H4a-c: Cognitive, Affective, and Behavioral Engagement positively influence Brand Loyalty.

3. RESEARCH METHODOLOGY

3.1 Study design and data collection

The research study employed a cross-sectional survey method and surveyed Xiaomi smartphone users in Erbil. The data were gathered by employing a hybrid method of collection (online & offline or O2O) and distributing the online survey questionnaire using informed consent and sampling randomly. The survey questionnaire contained five components: a demographic part, questions on the current device, experiences of marketing with AI, brand engagement, and brand loyalty. The data was collected to examine the relationships between these constructs. The sample is diverse across key demographic variables and provides a representative view of Xiaomi's customer base in the region.

3.2 Measures and instrumentation

The latent variables in the model were measured through multi-item scales adapted from prior literature (full details are provided in survey questionnaire). Each perceptual and engagement construct were measured on a 5-point Likert scale, where 1 = Strongly Disagree and 5 = Strongly Agree. The loyalty construct was measured through a Likert-scale statement, (My next smartphone will very likely be another

Xiaomi") as well as a 0-10 scale (where 0 = not at all likely to recommend and 10 = extremely likely to recommend).

The actual items for each of the constructs are as follows:

- Perceived Personalization: Items 8, 9, 10.
- Recommendations: Items 11, 12, 13.
- Chatbot Experience: Items 14, 15, 16.
- Cognitive Engagement: Items 17,18, 19.
- Affective Engagement: Items 20, 21, 22.
- Behavioral Engagement: Items 23, 24, 25.
- Loyalty: items 26, 27.

3.3 Data analysis method

Data analysis was conducted using the SmartPLS 4 program. There is considerable appeal in applying this powerful multivariate analysis technique because its reasonably determinants predictive research, and can address complicated models with smaller sample sizes, or models that draw on non-normality in data distribution (Hair et al., 2014; Hair et al., 2011). Data analysis followed a two-step assessment. First, the measurement model was investigated for reliability and validity. Second, the structural model was evaluated to test the hypothesized relationships and overall predictive validity of the model.

4. RESULTS

4.1 Descriptive statistics

Responses were analyzed from a total of 384 people. Table 1 presents a demographic analysis of the sample. The sample included mostly 18-24 year-olds (43%), and a sizable number of 25-30 year-olds (29%). In terms of gender distribution, the sample was predominately male (72%). The most common occupation amongst participants was 'Employed (Professional/Office)' at 37% of participants, followed by 'Student' at 30% of participants. The distribution of monthly income was heavily concentrated in the '<750,000' IQD range (37%). The key purchase motivations are "Price/Value" (49%) and "Features/Specs" (20%), underscoring the brand's market positioning.

TABLE 1. PARTICIPANT DEMOGRAPHICS AND PURCHASE BEHAVIORS

Variable	Category	Frequency	Percentage
Age Group	18-24	165	43%
	25-30	112	29%
	31-40	83	22%
	41 or older	24	6%
Gender	Male	276	72%
	Female	108	28%
Occupation	Employed (Professional/Office)	142	37%
	Student	116	30%
	Self-Employed/ Business Owner	78	20%
	Other	48	13%
Monthly Income	<750,000	143	37%
	750,001-1,500,000	98	26%
	1,500,001-3,000,000	79	21%
	>3,000,000	64	17%
Model	Redmi Note 12	132	34%
	Redmi 12C	81	21%
	Xiaomi 13T	42	11%
	POCO F6	36	9%
	POCO X5 Pro	28	7%
	OTHERS	65	17%
Ownership Duration	<6 months	54	14%
	6 months - 1 year	86	22%
	1-2 years	103	27%
	>2 years	141	37%
Purchase Reason	Price/Value	187	49%
	Features/Specs	76	20%
	Recommendation	69	18%
	Previous Experience	42	11%
	Design	10	3%

Source: Prepared by the authors

4.2 Measurement model evaluation

Reliability and validity of the measurement model were evaluated using several key metrics. Results in Table 2 demonstrate that all constructs are reliably and validly measured.

TABLE 2. THE RELIABILITY AND VALIDITY OF THE MEASUREMENT MODEL

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Affective	0.830	0.831	0.898	0.746
Chatbot	0.852	0.854	0.910	0.772
Cognitive	0.799	0.813	0.881	0.713
Loyalty	0.737	0.738	0.884	0.791
Personalize	0.840	0.843	0.904	0.758
Recommendations	0.851	0.854	0.910	0.771

Source: Prepared by the authors based on the outputs of the statistical program SmartPLS 4

All constructs showed high internal consistency as evidenced by Cronbach's alpha coefficients of 0.737 to 0.852 on a range of 0 to 1, significantly greater than a soundness threshold of 0.70. Measures of composite reliability (rhoc) are used as better, more robust estimates of reliability, and rhoc values ranging from 0.884 to 0.910, also indicating reliability of scales.

Convergent validity was established by measure of Average Variance Extracted (AVE). All AVE estimates exceeded the cut-off of 0.50, from 0.713 (Cognitive) to 0.791 (Loyalty), which satisfied the technical guidelines stipulated the percentage of variance captured by the corresponding indicator variables.

We confirmed discriminant validity using the Fornell-Larcker criterion that checks if the square root of the AVE of each construct is greater than the correlation that it has with any other construct (Fornell and Larcker, 1981). These values are profiled in Table 4; the square root of the AVE for each construct (i.e. diagonal values) are greater than the corresponding inter-construct correlations (i.e. off-diagonal values) indicating each construct in the model is a clearly distinct construct.

4.3 Structural model assessment

The structural model fit the data well. The model fit summary is shown in Table 3. The value for Standardized Root Mean Square Residual (SRMR) was 0.054, which is well below the 0.08 level considered as good fit between model and data. The Normed Fit Index (NFI) value of 0.830 is below the ideal value of 0.90, but indicates an acceptable level of fit.

TABLE 3. STRUCTURAL MODEL FIT

	Saturated model	Estimated model
SRMR	0.051	0.054
d_ULS	0.551	0.620
d_G	0.504	0.538

Source: Prepared by the authors based on the outputs of the statistical program SmartPLS 4

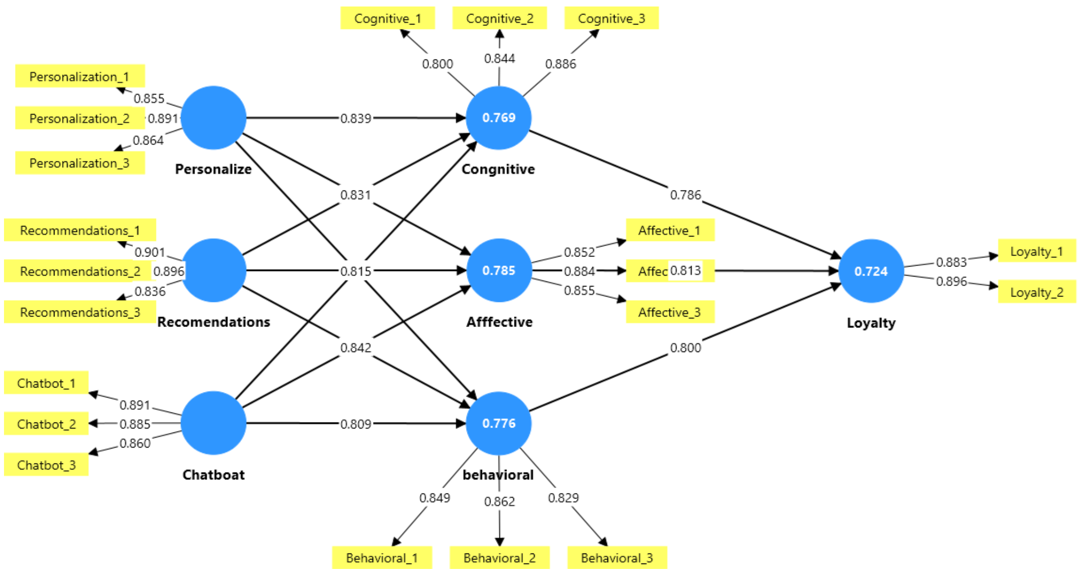

FIGURE 1. THE OUTER LOADINGS, R-SQUARE AND CORRELATIONS
Source: Prepared by the authors based on the outputs of the statistical program SmartPLS 4

Business Excellence and Management
Volume 15 Issue 3 / September 2025

The predictive ability of the model was determined through the R-square for the endogenous variables. The results are quite strong, demonstrating that the model predicted a sizeable proportion of the variance in the dependent variables. The R-square for Affective Engagement is 0.785, followed by Cognitive Engagement (0.769), Behavioral Engagement (0.776), and Brand Loyalty (0.724) indicating highly explanatory power of the model and confirmed the significance of the selected predictors. The Outer Loadings for each indicator are in Figure 1 and were depicted in the measurement model visual.

4.4 Hypothesis testing and path analysis

All hypothesized paths were statistically significant at a 0.000 p-value, which confirms the proposed direct relationships shown in the model in its extensiveness, while tables shown the results (including Path Coefficients +/- standard error, t-statistics, and R-square) are illustrated in Table 4. The structural model is presented visually with path coefficient and p-values.

The results identified the positive influence of all three AI marketing constructs (Chatbot, Personalization, Recommendations) on the three components of customer engagement (Cognitive, Affective, Behavioral). The path from Chatbot to Affective engagement had the strongest coefficient of 0.405, while Recommendations to Behavioral engagement also had a strong coefficient of 0.390 were noted as strong supports. Therefore, AI marketing is not a singular tool, but an integrated system that can influence a customer's cognition, feelings and behaviors associated with the brand.

TABLE 4. TESTING THE HYPOTHESIS

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)
Affective -> Loyalty	0.380	0.380	0.054	7.020
behavioral -> Loyalty	0.290	0.290	0.051	5.663
Chatbot -> Affective	0.405	0.405	0.049	8.194
Chatbot -> behavioral	0.194	0.195	0.046	4.250
Chatbot -> Cognitive	0.240	0.241	0.049	4.929
Cognitive -> Loyalty	0.232	0.232	0.051	4.549
Personalize -> Affective	0.326	0.326	0.055	5.984
Personalize -> behavioral	0.346	0.345	0.049	7.098
Personalize -> Cognitive	0.345	0.344	0.050	6.877
Recommendations -> Affective	0.204	0.203	0.047	4.348
Recommendations -> behavioral	0.390	0.390	0.048	8.083
Recommendations -> Cognitive	0.342	0.342	0.046	7.454

Source: Prepared by the authors based on the outputs of the statistical program SmartPLS 4

The results indicate that all three AI marketing components (Chatbot, Personalization, Recommendations) have significant positive effects on all three dimensions of customer engagement (Cognitive, Affective, Behavioral). For instance, compared to the other AI marketing components, the path from Chatbot to Affective engagement has a large coefficient of 0.405 and the path from Recommendations to Behavioral engagement is still quite strong at 0.390. This suggests that AI marketing is not a siloed tool but rather an integrated system that can positively impact a customer's thinking, feeling, and doing. regarding the brand. The three dimensions of customer engagement create a positive impact on brand loyalty. The direct effect of affective engagement on loyalty stands at 0.380 while behavioral engagement has a path coefficient of 0.290 and cognitive engagement has a path coefficient of 0.232. The research outcome shows that customer emotional connection with a brand serves as the most powerful direct factor which drives future purchase decisions and recommendation of the brand (Cheng and Jiang, 2022).

4.5 Total effects analysis

As detailed previously, the perceived exogenous elements, directly or indirectly, affect the endogenous variables for measured impacts. According to table 5, personalization cumulatively impacts loyalty the most with a total value of 0.304. Recommendations, with 0.270, and Chatbot Experience, at 0.266, followed closely.

TABLE 5. THE TOTAL EFFECTS

	Total effects
Affective -> Loyalty	0.380
behavioral -> Loyalty	0.290
Chatbot -> Affective	0.405
Chatbot -> behavioral	0.194
Chatbot -> Cognitive	0.240
Chatbot -> Loyalty	0.266
Cognitive -> Loyalty	0.232
Personalize -> Affective	0.326
Personalize -> behavioral	0.346
Personalize -> Cognitive	0.345
Personalize -> Loyalty	0.304
Recommendations -> Affective	0.204
Recommendations -> behavioral	0.390
Recommendations -> Cognitive	0.342
Recommendations -> Loyalty	0.270

Source: Prepared by the authors based on the outputs of the statistical program SmartPLS 4

This observation marks an important difference between direct personalization and total impacts. Although the chatbot experience directly impacts affective engagement the most, personalization's reach is wider. Its substantial impact on all three types of engagement—cognitive (0.345), affective (0.326), and behavioral (0.346)—suggests cumulatively results in the strongest impact on loyalty. This indicates that personalization works primarily to leverage loyalty through a variety of interconnected engagement strategies.

5. DISCUSSION

5.1 Interpretation of key findings

This study corroborated the relationships put forth in the introduction and in AI-enabled marketing. It revealed in greater detail some of the relationships in AI marketing. As already mentioned in the analysis section, the analysis showed that the affective engagement, which is the customer's emotional connection to the brand, is the most significant direct predictor of brand loyalty. This is normally very notable, as it adds some depth and is a significant improvement to a purely transaction-based version of a customer relationship (Reichheld and Teal, 2001). It shows that although the functional elements of the product to be purchased such as product specification and pricing are considered to be major purchase drivers by the majority of this sample, the strongest drive of loyalty is something deeper, and emotional (Li, 2024 and Reichheld and Teal, 2001). As noted, for marketing managers, the implication is that the strategies aimed at the formation of a feeling of community, pride and belonging are most likely to be effective and the longest standing in both customer and company loyalty (Huang and Rust, 2021; Reichheld and Teal, 2001).

Second, it is clear from the path analysis that all AI marketing components are effective; however, the total effects analysis focuses on the particularly insightful role of perceived personalization. Perceived personalization stands out as the most influential factor driving brand loyalty because its effects span the entire engagement spectrum, including cognitive, affective, and behavioral engagement as triadic influences. When marketing communications are framed as personalized at an individual level, the brand strengthens emotional attachment and, in addition, makes consumers think on deeper levels, which drives them to assume a more proactive role as advocates of the brand (Chaffey and Ellis-Chadwick, 2019). This proves that the ability to nurture brand relationships and foster loyalty across levels of interaction makes brand personalization a fundamental strategic lever.

Finally, this study validates that AI-based marketing tools serve as a strong multiplier for engagement. The engagement constructs' high R-square values (76.9% to 78.5%) suggest that these tools have a significant efficiency in explaining a customer's engagement. This validates that a brand's AI marketing expense is not for a single purpose. Instead, it is a holistic system in which all parts—ranging from a responsive chatbot to pertinent recommendations—seamlessly engage in driving a customer's thoughts, feelings, and actions. The data demonstrates that a favorable chatbot encounter, for instance, not only makes a user feel good (affective) but also informs (cognitive) and increases the likelihood of brand interaction (behavioral), thus fueling a positive cycle of engagement.

5.2 Theoretical implications

This research offers some theoretical insights. It incorporates AI-driven marketing as an influential antecedent, thus integrating and extending the customer engagement-loyalty framework. The model captures the multidimensional AI customer engagement toolkit's impact on customer behavior, revealing its effects emerge from cognitive, affective, and behavioral filters. The results also elucidate the role of affective engagement as the strongest direct driver of loyalty, enhancing and refining the theoretical model of brand relationships in the digital era.

5.3 Managerial implications

Particularly marketing managers, especially those for Xiaomi in the Erbil market, emerge from this discussion with particular insights and implications for practice.

Strengthen Emotional Engagement: Considering the relationship between loyalty and affective engagement, marketing efforts should center around fostering a sense of community and brand pride (Li, 2024; Reichheld and Teal, 2001). Some of the options could include local user meetups, user-generated content showcasing on social media, and social brand narratives that align with local culture and values.

Invest in Comprehensive Personalization: Perceived personalization remains a critical driver of total loyalty. Rather than product purchases, marketing activities should focus on individualized tailored content, custom-designed emails, selective promotional offers, and customer interactions which treat customers as living human beings, not just a file number or a point on a graph (Kumar and Rajan, 2019; Weidig et al., 2024). Implementing this approach, over social media and other digital channels, will construct loyalty in many ways through multi-dimensional engagement.

Enhance Chatbot Responsiveness and Capability: The strong direct link between the chatbot experience and the affective engagement suggests the chatbot experience impacts emotional engagement deeply and a well thought out and truly useful chatbot turns out to be an effective means of developing emotional bonds (Hsu and Lin, 2023). Decision makers should spend on AI-driven support which responds in a timely and effective manner and goes well beyond passing brand-related information to offer warm and emotionally valued help (Hsu and Lin, 2023).

6. LIMITATIONS AND FUTURE RESEARCH

There are limitations to this study. Because of a cross-sectional design, this study can demonstrate relationships but cannot establish definitive causality. A longitudinal design would be able to capture how these relationships change over time. This study is also limited to a specific region, Erbil, and a specific

Business Excellence and Management
Volume 15 Issue 3 / September 2025

Business Excellence and Management
Volume 15 Issue 3 / September 2025

brand, Xiaomi. This would affect how generalizable these findings are. There is an opportunity to carry out comparative studies across multiple regions and different brands to better test the robustness and universality of the model proposed. Furthermore, the authors of this proposal can explore the mediating effects of perceived quality and trust on the relationship between AI-driven marketing and customer engagement (Al-Adwan and Al-Horani, 2019; Nazir et al., 2023).

7. CONCLUSION

The smartphone market in Erbil is the focus of a detailed and evidenced examination of the flow of AI-driven marketing, consumer engagement, and brand loyalty which has been presented in this study. Through the meaningful and interdependent chatbot experience, personalization, and recommendation which are integral features identified, a strong theoretical model and actionable guidance for marketing practitioners has been developed. The findings underscore that a strategic, emotionally resonant, and personalized approach to AI marketing is not just a trend but a powerful and proven strategy for cultivating deep and lasting brand loyalty.

REFERENCES

Aaker, D. A. (1991). Managing brand equity: Capitalizing on the value of a brand name. New York, NY: Free Press.

Adam, M., Wessel, M., & Benlian, A. (2021). AI-based chatbots in customer service: Their impact on user experience and companies' profitability. Journal of Service Management, 32(2), 203–220.

Al-Adwan, A. S., & Al-Horani, A. T. (2019). The impact of trust on online repurchase intention: A study on Jordanian customers. Journal of Strategic Marketing. https://doi.org/xxxx

Anderson, A., Brown, J., Chen, R., & Lee, T. (2020). The importance of digital marketing in modern business. Journal of Marketing Strategy.

Brodie, R. J., Hollebeek, L. D., Juric, B., & Ilic, A. (2011). Customer engagement conceptual domain, fundamental propositions, and implications for research. Journal of Service Research, 14(3), 252–271.

Brown, A., & Thompson, S. (2023). The digital customer journey: An AI perspective. Journal of Digital Marketing.

Chaffey, D., & Ellis-Chadwick, F. (2019). Digital marketing (7th ed.). Harlow, UK: Pearson Education.

Cheng, Y., & Jiang, H. (2020). The effect of AI marketing on brand loyalty. Journal of Product & Brand Management.

Cheng, Y., & Jiang, H. (2022). Customer–brand relationship in the era of artificial intelligence: Understanding the role of chatbot marketing efforts. Journal of Product & Brand Management.

Davenport, T. H., Guha, A., Grewal, D., & Bressgott, T. (2020). How artificial intelligence will change the future of marketing. Journal of the Academy of Marketing Science, 48(1), 24–42.

De Keyser, A., Li, X., Verbeeck, C., & Bijmolt, T. H. (2021). Personalization and recommendation algorithms in a retail context. Journal of Retailing.

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., ... & Williams, M. D. (2021). Artificial intelligence (AI) in marketing: A systematic review. Journal of the Academy of Marketing Science, 49(1), 1–26.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. Journal of Marketing Research, 18(1), 39–50.

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2014). A primer on partial least squares structural equation modeling (PLS-SEM). Thousand Oaks, CA: Sage Publications.

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed, a silver bullet. Journal of Marketing Theory and Practice, 19(2), 139–151.

Hasan, M., Ali, R., & Khan, S. (2021). Artificial intelligence services in the development of brand loyalty. International Journal of Marketing.

Hollebeek, L. D., Glynn, M. S., & Brodie, R. J. (2014). Consumer brand engagement in social media: Conceptualization, scale development and validation. Journal of Interactive Marketing, 28(2), 149–165.

Hsu, J., & Lin, C. (2023). The effect of AI chatbot service quality on user loyalty. Journal of Retailing and Consumer Services.

Huang, M. H., & Rust, R. T. (2021). A strategic framework for artificial intelligence in marketing. Journal of the Academy of Marketing Science, 49(1), 30–50.

Kumar, A., & Rajan, R. (2019). Leveraging AI for personalized customer experience. Journal of Marketing Research.

Li, S. S., & Karahanna, E. (2015). Online recommendation systems in a B2C e-commerce context: A review and future directions. AIS Electronic Library (AISeL).

Li, Y. (2024). The role of emotional marketing in building brand loyalty. Marketing Eye Atlanta Blog.

Maroufkhani, P., Ismail, W. K. W., Ghobakhloo, M., & Nilashi, M. (2022). AI assistants and customer loyalty. Journal of Retailing and Consumer Services.

Nazir, S., Shah, S. Z. A., & Malik, H. F. (2023). Sustainable customer relationships and brand loyalty. Journal of Retailing and Consumer Services.

Pravinkumar, M., & Chaurasia, S. (2023). Emerging smartphone market in Iraq: Unlocking opportunities for brands. Market Smartphone. Retrieved from https://www.canalys.com/insights/emerging-smartphone-market-in-iraq

Prentice, C., Chen, P. J., & Wang, X. (2020). The role of AI and staff service quality on customer satisfaction and loyalty. Journal of Retailing.

Pu, P., Chen, L., & Hu, R. (2018). Evaluating recommender systems from the user's perspective: Survey of the state of the art. RERO DOC Digital Library.

Reichheld, F. F., & Teal, T. (2001). The loyalty effect: The hidden force behind growth, profits, and lasting value. Boston, MA: Harvard Business School Press.

Saunders, M., Lewis, P., & Thornhill, A. (2019). Research methods for business students (8th ed.). Harlow, UK: Pearson Education.

Smith, M. D., Bailey, J., & Brynjolfsson, E. (2000). The effectiveness of personalized recommendations in online retailing. Journal of Management Information Systems.

Statcounter Global Stats. (2025). Mobile vendor market share Iraq. Retrieved August 10, 2025, from https://gs.statcounter.com/vendor-market-share/mobile/iraq

Steffi, G., Arun, K., & Singh, R. (2024). AI-enabled marketing strategies to improve customer satisfaction and loyalty. Journal of Business Research.

Vivek, S. D., Beatty, S. E., Dalela, V., & Morgan, R. M. (2014). A generalized multidimensional scale for measuring customer engagement. Journal of Marketing Theory and Practice, 22(4), 401–420.

Weidig, E., Weippert, M., & Kuehnl, M. (2024). Personalization and loyalty. Journal of Digital Marketing.

Yang, S., Kim, H., Lee, Y., & Park, J. (2023). The role of AI in personalizing customer engagement. International Journal of Electronic Commerce.

Zhou, L., & Duan, W. (2020). The impact of AI-driven marketing on customer satisfaction. Journal of Interactive Marketing.