Research Article

Received: 19 June 2026
Accepted: 30 October 2026
Published: 02 November 2026

AI-Based Customer Service and Brand Loyalty in Saudi Retail: An Empirical Investigation of the Service Quality–Emotional Attachment–Loyalty Pathway in 2025–2026

Heyam Almousa
Department of Marketing, College of Business, King Saud University, Riyadh, Saudi Arabia.
healmousa@ksu.edu.sa

Cite this article:
Heyam Almousa (2026). AI-Based Customer Service and Brand Loyalty in Saudi Retail: An Empirical Investigation of the Service Quality–Emotional Attachment–Loyalty Pathway in 2025–2026. Revista Cultura Científica, (24), pp. 2194–2207. https://doi.org/10.70517/revcc2624179

2026 © The Author(s). Published by Revista Cultura Científica. This article is published as open access under the Creative Commons Attribution 4.0 International (CC BY 4.0) license (http://creativecommons.org/licenses/by/4.0/).

Abstract

Artificial intelligence (AI)-powered customer service systems have expanded across Saudi Arabia's retail sector during 2025–2026, with major retailers increasingly exploring chatbots, recommendation engines, and automated service technologies. Official Saudi digital-economy statistics document the wider shift towards digital commerce, although online-shopping participation should not be interpreted as a direct measure of AI adoption or retailer-specific investment. This study examines the relationship among AI service quality, emotional brand attachment, and brand loyalty using survey results reported for 512 retail customers in Riyadh, Jeddah, and Dammam, collected between May and September 2026. Using partial least squares structural equation modelling (PLS-SEM) and bootstrap resampling, the analysis reports a positive direct association between AI service quality and loyalty ($\beta = 0.421$, $p < 0.001$), together with a positive indirect association through emotional brand attachment (reported indirect effect $= 0.238$, 95% CI [0.187, 0.289]). The study considers a possible "mechanical efficiency paradox": functional improvements in AI service may be more strongly associated with loyalty than with emotional attachment. Importantly, this survey does not include a direct comparison with human-delivered service, and the reported positive attachment coefficient ($\beta = 0.187$) cannot establish that AI decreases attachment. The reported gender subgroup estimates differ: the AI quality–attachment association is positive for male respondents ($\beta = 0.289$, $p = 0.001$) and statistically nonsignificant for female respondents ($\beta = -0.023$, $p = 0.811$). Age-specific estimates also vary, with more positive reported coefficients in younger groups, although the statistical significance of the age differences requires further supporting output. The manuscript reports that the model accounts for 51.2% of the variance in loyalty ($R^2 = 0.512$) and has positive predictive relevance ($Q^2 = 0.289$). Because some path estimates, correlations, and variance-explained values are not mutually consistent, these results require rechecking against the original SmartPLS output before publication. Managerial implications include offering hybrid AI–human service, allowing customers to choose their preferred channel, and maintaining personal attention for complex or emotionally sensitive interactions. The findings provide a framework for assessing how technological service quality and relationship-building might jointly contribute to brand loyalty.

Keywords: AI service quality, emotional brand attachment, brand loyalty, technology adoption, service quality paradox

1. INTRODUCTION

The Saudi Arabian retail sector provides an important setting for examining the relationship between digital service delivery and customer loyalty during 2025–2026. The Communications, Space and Technology Commission's *Saudi Internet 2025* report documents widespread participation in online commerce, including an online-shopping participation rate of 76.9% among internet users [1]. This indicator measures online shopping rather than retailers' adoption of AI-based customer service, and the two measures should be distinguished. Nevertheless, the expansion of digital commerce creates incentives for retailers to consider automated support, relevant personalisation, and coordinated service across multiple channels. National adoption rates and investment totals cannot be inferred from online-shopping participation alone; they require separate primary evidence with clearly specified populations, time periods, definitions, and measurement procedures.

The selected commercial context includes digital marketplaces such as Noon, booksellers such as Jarir, and supermarket operators such as Carrefour. Recommendation systems, customer-support tools, and automated checkout are distinct forms of service innovation that may be relevant to these settings. Their availability and use should be documented at the level of the participating organisation and service encounter, rather than assumed from a brand's general digital presence. The sampling description also includes Al Hokair, making it necessary to identify the participating business units precisely. Retail purchases and hospitality encounters should be distinguished analytically, even when a diversified corporate group operates in both sectors, because customer expectations and service objectives may differ.

AI-based customer-service tools may improve operational efficiency by offering rapid responses, continuous availability, and automated access to relevant information. Whether a particular retailer achieves these benefits depends on implementation quality, customer needs, information accuracy, escalation procedures, and integration with human agents. Response time, recommendation satisfaction, service accuracy, complaint volume, and checkout duration represent different performance indicators and should be measured separately. The present questionnaire does not supply independently inspectable company records for these operational outcomes. Consequently, improvements in such indicators remain possible benefits that motivate the study, rather than verified corporate performance changes that can be attributed to the participating retailers.

At the same time, improving operational metrics does not automatically guarantee stronger relationships between customers and brands. Customers may value a service that is efficient while still preferring personal attention for emotionally sensitive situations, unresolved complaints, or complex purchase decisions. Whether a specific retailer experienced declining attachment scores, repeat-purchase rates, or customer lifetime value would require longitudinal or transactional evidence. The present cross-sectional survey cannot directly establish those changes; rather, it motivates an investigation into the possible difference between functional service evaluations and emotional brand attachment.

Recent peer-reviewed research has examined relationships between AI-assisted communication and consumers' emotional responses. Kirk and Givi [2] found that attributing emotional marketing communications to AI can reduce favourable consumer responses under particular experimental conditions. Sheng, Natalia, and Rusfian [3] compared chatbot, augmented, and human service interactions and showed that customer–brand relationships depend on the service context. These findings support examining operational efficiency and relational quality as distinct considerations. Their experimental settings and outcome measures differ from those of the present survey, however, and they should not be interpreted as evidence that every AI-based service interaction necessarily weakens emotional brand attachment.

In the Saudi retail context, it is therefore useful to examine whether consumers evaluate AI service based on its accessibility, speed, and consistency while separately considering empathy, cultural appropriateness, and personal recognition. The balance between these dimensions may vary across customers, brands, and types of service encounters. Whether these expectations differ significantly by age, gender, or prior experience is an empirical question rather than a universal characteristic of those groups.

The theoretical distinction underlying the proposed paradox concerns functional and relational components of loyalty. Functional loyalty can reflect evaluations of service convenience, availability, and perceived usefulness, whereas relational loyalty involves affective bonds and a sense of attachment to the brand. AI systems may support the former through rapid information processing, but they may also support or hinder the latter depending on service design and the surrounding human support. The SERVQUAL framework developed by Parasuraman, Zeithaml, and Berry [4] encompasses reliability, responsiveness, assurance, empathy, and tangibles. Empathy is therefore part of the traditional model, not an entirely absent component. The central research question is how these dimensions are expressed or perceived when part of the customer-service encounter is automated.

This study addresses three interrelated research questions concerning consumer evaluations of AI-enabled services in the contemporary Saudi retail environment:

RQ1: Is perceived AI service quality positively associated with brand loyalty in Saudi retail, and what direct and attachment-related pathways are consistent with the observed associations? Can the survey distinguish a direct statistical

pathway from the pathway passing through emotional brand attachment?

RQ2: Does emotional brand attachment statistically mediate the relationship between AI service quality and brand loyalty, and does the reported decomposition suggest partial rather than complete mediation? What assumptions and additional evidence are needed to interpret this cross-sectional mediation model?

RQ3: Do the reported associations differ across respondents' age, gender, digital literacy, and prior AI experience? Which moderating associations have actually been estimated and tested, and which remain questions for subsequent research?

This research seeks to contribute to retail service-quality literature in several respects. First, it investigates the possibility that customer satisfaction with efficient AI service may differ from emotional attachment to the retail brand, a distinction referred to here as the proposed "mechanical efficiency paradox." The current findings indicate a positive, rather than negative, overall association between AI service quality and emotional attachment, so the paradox must be understood as a possible difference in the relative strength of associations, not a demonstrated reduction in attachment. Second, the paper places these questions in a Saudi retail setting and considers a contemporary survey period, although any claim to be the first study in the region would require a systematic review of earlier research.

Third, from a methodological perspective, the study specifies a single-mediator model together with gender and age subgroup comparisons. This is simple mediation rather than serial mediation, because only one intervening construct is included. Fourth, the study identifies practical issues for retail managers who must coordinate automated support with human-led relationship management, although the proposed recommendations should remain provisional until the reported model estimates have been reconciled and the original research data checked.

2. THEORETICAL FRAMEWORK AND HYPOTHESIS DEVELOPMENT

2.1. SERVICE QUALITY THEORY AND AI SERVICE CHARACTERISTICS

The service-quality literature, including the SERVQUAL framework of Parasuraman, Zeithaml, and Berry [4], identifies five broad dimensions: (1) reliability, or the ability to deliver a promised service dependably and accurately; (2) responsiveness, or willingness to assist customers promptly; (3) assurance, which includes competence, courtesy, and the ability to inspire confidence; (4) empathy, referring to caring and individualised attention; and (5) tangibles, such as facilities, equipment, and communication materials. Brady and Cronin [5] provide a related hierarchical conceptualisation of service quality, while Zeithaml, Parasuraman, and Malhotra [6] examine how customers evaluate service delivered through websites. Together, these sources help justify considering both operational and interpersonal aspects of AI-mediated service.

AI service systems may display a distinctive profile across these dimensions. For reliability, automation can make responses more consistent when information is accurate, current, and appropriately verified. However, AI responses are not guaranteed to be error-free, and system failures, inconsistent outputs, or outdated information can compromise reliability. Thus, it would be inaccurate to state that AI categorically eliminates human error or always provides identical service quality irrespective of context.

Regarding responsiveness, chatbots may offer around-the-clock access and reduce waiting times for routine requests, provided the system is operational and can escalate difficult cases effectively. Regarding assurance, automated tools can provide rapid access to product and policy information, but transparency and confidence remain important considerations. Tangibles may include the interface and accessibility of the technology rather than being wholly irrelevant to digital service. Finally, AI systems can simulate empathic language, although customers may evaluate such responses differently from empathy expressed by a human employee. These distinctions warrant empirical assessment rather than categorical claims of universal superiority or deficiency.

H1: Perceived AI service quality is positively associated with brand loyalty ($\beta > 0$, $p < 0.05$). Despite possible limitations in individual service dimensions, favourable service evaluations are expected to correspond to stronger loyalty intentions, especially through convenience and perceived functionality.

2.2. EMOTIONAL BRAND ATTACHMENT AND RELATIONAL LOYALTY

Emotional brand attachment describes the affective bond that consumers develop with a brand, including feelings of closeness, connection, and identification. Thomson, MacInnis, and Park [7] developed and validated a measure of this construct; Park and colleagues [8] subsequently distinguished attachment from brand attitude strength. Work on long-term online relationships, such as Bauer, Grether, and Leach [9], also demonstrates the importance of trust and commitment in technology-mediated exchange. Attachment differs from a rational evaluation of service efficiency, and it may be associated with behavioural loyalty, advocacy, and resilience in the face of competing offers. The strength of those consequences nonetheless depends on the consumer and service setting, so broad numerical claims about lifetime value require specific supporting evidence.

More recent scholarship suggests that technological convenience and emotional connection need not change in parallel. Consumers might appreciate immediate responses and consistent information while still valuing personal assistance for problems involving uncertainty, frustration, or high perceived risk [2, 3]. This possibility creates an important strategic question for retailers: whether improving digital service quality produces comparable gains in the emotional and functional dimensions of loyalty. Importantly, a weaker positive association is not equivalent to a decline in emotional attachment, and this distinction governs the interpretation of the present model.

H2: Emotional brand attachment statistically mediates the association between AI service quality and brand loyalty, with both a direct association and an indirect association through attachment (expected indirect effect $> 0, p < 0.05$). Such a model describes the pattern of covariance, but causal mediation requires assumptions that a cross-sectional questionnaire alone cannot establish.

H3: Perceived AI service quality is positively associated with emotional brand attachment ($\beta > 0, p < 0.05$), although this association may be smaller than the direct association between service quality and loyalty. The comparison is treated as a testable statistical expectation rather than proof that AI systems cannot support emotionally meaningful customer experiences.

2.3. DEMOGRAPHIC MODERATION: GENDER DIFFERENCES IN THE OBSERVED ASSOCIATIONS

Differences between consumers in preferred service styles may reflect many individual and contextual factors, including customer expectations, previous service experiences, cultural norms, and familiarity with technology. Williams and Spiro [10] examined communication style in salesperson–customer interactions, providing a basis for considering interpersonal differences in service encounters. That study does not, however, establish an invariant preference for empathy among women or efficiency among men. The present analysis examines reported gender differences as sample-specific moderation findings rather than as fixed psychological characteristics of either group.

Applied to AI-mediated service, this perspective suggests that the relationship between perceived quality and emotional attachment may vary between demographic subgroups. Differences should be tested directly rather than inferred from stereotypes concerning how men or women are expected to respond. Personalisation and channel choice should therefore follow customers' expressed needs and preferences, not a predetermined assumption based solely on their gender.

H4: The association between perceived AI service quality and emotional brand attachment differs across the gender groups represented in the survey (moderation effect $p < 0.05$). The hypothesis concerns an empirical difference in coefficients and does not presume that the direction of each subgroup association is universal.

2.4. AGE MODERATION AND DIFFERENCES IN TECHNOLOGY EXPERIENCE

Age and accumulated digital experience may help explain variation in comfort with technology-mediated interactions. Some younger consumers have encountered algorithmic services throughout much of their adult lives, while some older consumers may place greater value on familiar human-service channels. These are tendencies worth investigating, not inherent capabilities or preferences of any age category. Age also intersects with accessibility, digital literacy, prior AI exposure, and the nature of the requested service; therefore, the labels "digital native" and "digital immigrant" should not be treated as substitutes for measured experience.

In retail services, it is therefore plausible that the strength of association between perceived AI service quality and customer outcomes varies across age groups. Younger respondents may respond favorably to convenience, and some older respondents may value greater access to human assistance. However, individual preferences can differ considerably within each age group, and the present questionnaire provides no direct randomised comparison of AI-only versus human-only service.

H5: Age moderates the associations between perceived AI service quality, emotional attachment, and brand loyalty, with the hypothesis that the estimated relationships vary across respondent age groups (moderation effect $p < 0.05$). The age groups and comparison statistics must be specified consistently before a claim about monotonic age-related differences can be established.

3. METHODOLOGY

3.1. RESEARCH DESIGN, SAMPLING, AND DATA COLLECTION

This research used a cross-sectional, quantitative survey design. The manuscript reports that data were collected from May to September 2026, a five-calendar-month span when both end months are included. Recruitment was described as a multi-stage stratified process across three major Saudi cities: Riyadh ($n = 287$), Jeddah ($n = 156$), and Dammam ($n = 69$), together accounting for 512 participants. The reported proportions were approximately 56.1%, 30.5%, and

13.5%, respectively. The original recruitment documentation, sampling frames, and selection probabilities were not supplied; consequently, the claim of formal probability-based stratification requires author verification.

Participants were reportedly recruited through intercept surveys at retail-related locations described as using AI-enabled service systems. The manuscript identifies Noon ($n = 187$), Jarir ($n = 156$), Carrefour ($n = 96$), and Al Hokair ($n = 73$), totaling 512 respondents. These numbers are retained as author-reported sample allocations. Verification is needed for the precise names and existence of the reported recruitment sites, particularly the description of "Noon e-commerce flagship stores," and for the inclusion of hospitality facilities within a study presented as retail-only. The recruitment method should be described as purposive or intercept-based unless documented probability sampling was actually implemented.

The reported inclusion criteria were: (1) age 18 years or older; (2) residence in Saudi Arabia, including expatriate residents with at least 12 months of residence; (3) a purchase from a participating retailer within the preceding three months; (4) use of an AI customer-service feature, such as a chatbot, recommendation engine, voice assistant, or AI-recommended product, within the same period; (5) sufficient Arabic or English proficiency to understand the questionnaire; and (6) willingness to complete a survey requiring approximately 12–15 minutes. The operational definition of AI service exposure should be clarified to ensure that the different technologies constitute comparable experiences.

The reported demographic profile was as follows: age 18–25 years (24%, $n = 123$), 26–35 years (35%, $n = 179$), 36–45 years (22%, $n = 113$), 46–55 years (12%, $n = 61$), and 55 years or older (7%, $n = 36$); gender: male (58%, $n = 297$) and female (42%, $n = 215$); education: high school (12%, $n = 61$), bachelor's degree (58%, $n = 297$), and postgraduate education (30%, $n = 154$). Digital literacy was described as high (61%, $n = 312$), medium (28%, $n = 143$), or low (11%, $n = 56$), although these counts total only 511 and require correction from the original data. Prior AI experience was reported as extensive (34%, $n = 174$), moderate (42%, $n = 215$), or limited (24%, $n = 123$). Monthly retail spending categories were SAR 5,000–10,000 (18%, $n = 92$), SAR 10,001–20,000 (41%, $n = 210$), SAR 20,001–35,000 (28%, $n = 143$), and above SAR 35,000 (13%, $n = 67$). The apparent overlaps in the age category "46–55" and "55+" should also be clarified.

3.2. MEASUREMENT INSTRUMENTS AND SCALE DEVELOPMENT

AI service quality (ASQ) was assessed using a six-item measure: α=0.891, CR=0.912, AVE=0.676: All items were measured on a seven-point Likert scale (1 = strongly disagree; 7 = strongly agree):

- ASQ1: "AI customer service responds quickly to my inquiries and requests"
- ASQ2: "AI service is reliable and consistent in its responses and recommendations"
- ASQ3: "AI recommendations and suggestions match my personal preferences accurately"
- ASQ4: "AI service is available 24/7 when I need assistance"
- ASQ5: "AI service understands my needs and provides relevant assistance"
- ASQ6: "AI service provides practical and effective solutions to my problems"

Emotional brand attachment (EBA) was assessed using a seven-item measure: α=0.924, CR=0.936, AVE=0.708:

- EBA1: "I feel emotionally attached to this retail brand"
- EBA2: "This brand makes me feel good and valued as a customer"
- EBA3: "I love this brand and enjoy shopping there"
- EBA4: "I miss this brand when I haven't visited recently"
- EBA5: "I feel a special personal connection to this brand"
- EBA6: "This brand is like a trusted friend to me"
- EBA7: "I cannot imagine switching to a different retailer"

Brand loyalty (BL) was assessed using a six-item measure: α=0.901, CR=0.918, AVE=0.693:

- BL1: "I intend to continue purchasing from this brand in the future"
- BL2: "I recommend this brand to my friends and family"

- BL3: “I am deeply loyal to this brand”
- BL4: “I would defend this brand and its reputation to others”
- BL5: “I would not switch to a competitor even if they offer similar products” (reverse: “I would consider switching if competitor offers better AI service”)
- BL6: “This is my preferred retailer of choice”

The manuscript reports that the instruments were translated into Arabic through a standard back-translation procedure, beginning with professional translation from English, followed by independent back-translation into English. The reported process included reconciliation of discrepancies, a cultural-appropriateness review by a Saudi academic panel, and pilot testing with 40 consumers to evaluate clarity and comprehension. Documentation of the translated items, panel composition, and pilot feedback would strengthen reproducibility and permit independent assessment of the cultural adaptation process.

3.3. STRUCTURAL EQUATION MODELING AND ANALYSIS STRATEGY

The analysis was reported to use partial least squares structural equation modelling (PLS-SEM) in SmartPLS 4. The stated rationale emphasised prediction and the estimation of direct, indirect, and moderating associations in a sample of $N = 512$. This rationale should be related to the measurement structure, theoretical objectives, and documented distributional characteristics of the actual constructs: perceived AI service quality, emotional brand attachment, and brand loyalty. A sample of this size does not, by itself, establish that one estimation approach is preferable to every alternative. Similarly, the presence of interaction terms does not automatically justify a general claim of methodological superiority. Complete software settings and model specifications are necessary to assess the suitability and reproducibility of the reported estimation procedure.

For the measurement-model assessment, reliability was evaluated using Cronbach’s α (threshold ≥ 0.70; reported values 0.891–0.924) and composite reliability (threshold ≥ 0.70; reported values 0.912–0.936). Convergent validity was assessed using average variance extracted (AVE; threshold ≥ 0.50; reported values 0.676–0.708). The Fornell–Larcker comparison assesses whether each construct’s square root of AVE exceeds its correlations with the other constructs [11]. These summary measures address different measurement properties and should be interpreted together with indicator loadings and construct definitions. Because indicator-level data and complete estimation output were unavailable, the reported values cannot be independently recomputed from the manuscript alone. Furthermore, passing the Fornell–Larcker comparison does not conclusively establish discriminant validity in every measurement setting; the heterotrait–monotrait ratio offers an additional assessment [12].

The structural model was reportedly estimated using 5,000 bootstrap resamples and bias-corrected confidence intervals. The specified simple mediation analysis distinguished the direct association between service quality and loyalty from the indirect association passing through emotional brand attachment, with a reported total effect equal to the sum of these components. Moderation was examined using product-term interactions and group-level estimates. The manuscript should provide the exact coefficient scale, indicator coding, variable standardisation, and SmartPLS settings, especially because the reported path coefficients do not fully reconcile with the displayed correlation matrix.

The model-evaluation summary includes the standardised root mean square residual (SRMR), a goodness-of-fit (GoF) index, coefficients of determination, a reported Q^2 statistic, and the root mean square error of approximation (RMSEA). These statistics address different aspects of model assessment and cannot be treated as interchangeable evidence of validity. In particular, the GoF index is not suitable as a general model-validation criterion for PLS path models [13]. The reported RMSEA requires identification of the estimator and output from which it was obtained; no covariance-based estimation procedure is documented here. The account of Q^2 also requires clarification: SmartPLS documentation states that blindfolding was removed from SmartPLS 4 [14]. The reported value must therefore be linked to its actual software version and procedure. It cannot be relabelled as an out-of-sample predictive result without the corresponding analysis.

4. RESULTS

4.1. DESCRIPTIVE STATISTICS AND INTERCONSTRUCT CORRELATIONS

The principal descriptive results are summarised in Table 1.

The values in Table 1 describe generally favourable responses within this sample, with the highest mean for perceived AI service quality. Differences between construct means are descriptive; no paired comparison test is reported, and the constructs measure different aspects of the customer relationship.

The interconstruct correlations and discriminant-validity comparisons are presented in Table 2.

The correlations in Table 2 are positive, with the largest displayed association between emotional attachment and

Table 1. *Descriptive statistics for the main study constructs*

Variable	Mean	SD	Skewness	Kurtosis	Range
AI service quality	5.23	1.12	-0.34	-0.21	1-7
Emotional attachment	4.56	1.34	-0.18	-0.78	1-7
Brand loyalty	4.89	1.28	-0.42	-0.56	1-7

Note: $N = 512$. All variables were measured using seven-point Likert-type response scales.

Table 2. *Interconstruct correlations and discriminant validity*

Construct	ASQ	EBA	BL
AI service quality (ASQ)	(0.822)	0.412	0.534
Emotional attachment (EBA)	0.412	(0.841)	0.723
Brand loyalty (BL)	0.534	0.723	(0.833)

Note: Diagonal values in parentheses are square roots of AVE. All off-diagonal correlations are reported as significant at $p < 0.001$. The square root of AVE exceeds the displayed interconstruct correlations, satisfying this comparison; this result alone does not conclusively establish discriminant validity.

loyalty. Their proximity to the AVE-based diagonal values should be assessed alongside indicator content, especially where attachment and loyalty items refer to similar switching intentions.

As shown by the descriptive statistics in Table 1, the AI service-quality mean ($M = 5.23$) exceeds the midpoint of a seven-point response scale, which is 4.0 for the response scale used in this survey. This suggests a generally favourable evaluation of AI-service functionality among the surveyed respondents. Emotional attachment ($M = 4.56$) and brand loyalty ($M = 4.89$) are also above the scale midpoint, although a mean score alone cannot determine whether attachment is strong or weak. Table 2 reports positive correlations between service quality and attachment ($r = 0.412$), between service quality and loyalty ($r = 0.534$), and between attachment and loyalty ($r = 0.723$). These relationships motivate analysis of the statistical mediation model, but the correlation matrix must be reconciled with the reported path coefficients before stronger conclusions can be drawn.

4.2. MEASUREMENT MODEL ASSESSMENT RESULTS

The reported measurement-model statistics suggest satisfactory internal consistency and convergent validity according to the stated summary criteria. Cronbach's alpha was 0.891 for AI service quality, 0.924 for emotional attachment, and 0.901 for brand loyalty, with all values exceeding 0.70. Composite reliability estimates ranged from 0.912 to 0.936, and AVE values ranged from 0.676 to 0.708. These statistics are reported without changing their numerical values. Nevertheless, complete indicator loadings, cross-loadings, and analytical output were unavailable. The measurement assessment therefore remains dependent on the reported summaries rather than an independent recomputation of reliability and validity from the original responses.

The Fornell–Larcker comparison in Table 2 shows that each construct's square root of AVE exceeds its displayed correlations with the other constructs. For example, the AI service-quality diagonal value ($\sqrt{\text{AVE}} = 0.822$) exceeds its correlations with attachment ($r = 0.412$) and loyalty ($r = 0.534$). The corresponding comparisons also hold for attachment and loyalty. This is consistent with the stated numerical criterion, but it does not eliminate every possibility of conceptual or empirical overlap. An HTMT assessment, supported by the indicator-level data, would provide an additional examination of discriminant validity [12].

4.3. STRUCTURAL MODEL RESULTS: DIRECT AND INDIRECT EFFECTS

The reported direct, indirect, and total effects are presented in Table 3.

Table 3. *Author-reported direct, indirect, and total effects on brand loyalty*

Pathway	Effect type	Coefficient	SE	95% CI	t	p	Status
ASQ → BL	Direct	0.421	0.068	[0.288, 0.554]	6.19	<0.001***	✓ H1
ASQ → EBA → BL	Indirect	0.238	0.042	[0.187, 0.289]	—	<0.001***	✓ H2
ASQ → EBA	Pathway	0.187	0.074	[0.042, 0.332]	2.53	0.011*	✓ H3
EBA → BL	Pathway	1.274	0.089	[1.099, 1.449]	14.32	<0.001***	—
Total effect	Combined	0.659	0.071	[0.520, 0.798]	9.28	<0.001***	—

Note: ASQ = AI service quality; EBA = emotional brand attachment; BL = brand loyalty; SE = standard error; CI = confidence interval. Asterisks reproduce the reported significance levels: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. Hypothesis labels reproduce the reported decisions and remain provisional pending reconciliation of the model output.

The author-reported direct-effect estimate in Table 3 indicates a positive association between AI service quality and

brand loyalty ($\beta = 0.421$, $p < 0.001$). If the coefficient is standardised, a one-standard-deviation difference in perceived service quality corresponds statistically to a 0.421-standard-deviation difference in loyalty, conditional on the other model terms. However, the supplied coefficient requires verification because it does not reconcile readily with the displayed interconstruct correlations under the simple model described. A cross-sectional association cannot by itself demonstrate that a change in service quality would produce a corresponding change in customer loyalty.

The proposed "mechanical efficiency paradox" concerns the possibility that AI service quality is associated more strongly with direct loyalty intentions than with emotional attachment. The reported direct service-quality–loyalty coefficient ($\beta = 0.421$) exceeds the reported service-quality–attachment coefficient ($\beta = 0.187$). The manuscript also provides a difference statistic ($t = 2.89$, $p = 0.004$), but no procedure for comparing these coefficients is documented. This contrast does not establish that attachment decreases, that AI outperforms human agents, or that functional loyalty is causally generated by AI. Those claims would require an appropriate comparison group and a statistically coherent model.

The reported mediation estimates in Table 3 indicate an indirect association of 0.238 (95% CI [0.187, 0.289], $p < 0.001$). The author reports that this accounts for approximately 36% of the total effect ($0.238/0.659 \approx 0.36$), with the remainder attributed to the direct path. This arithmetic is internally consistent for the supplied total effect. However, the reported attachment-to-loyalty coefficient of 1.274 and the correlation matrix raise questions about whether all coefficients are standardised and estimated from the same model. The mediation interpretation should therefore be treated as provisional pending a check of the exported analysis results.

4.4. MODERATION ANALYSIS: GENDER AND AGE DIFFERENCES

The reported gender subgroup and interaction estimates are set out in Table 4.

Table 4. *Reported service-quality–attachment associations by gender*

Gender	ASQ → EBA (β)	SE	95% CI	t	p	n
Male	0.289	0.084	[0.124, 0.454]	3.44	0.001**	297
Female	-0.023	0.097	[-0.213, 0.167]	-0.24	0.811	215
Interaction	β=-0.312	0.102	[-0.512, -0.112]	-3.06	0.002	—

Note: SE = standard error; CI = confidence interval. The interaction coding and measurement invariance require verification. The table preserves the originally reported coefficients, uncertainty estimates, and significance markers.

As shown in Table 4, the reported service-quality–attachment coefficient was positive among male respondents ($\beta = 0.289$, $p = 0.001$), whereas the coefficient among female respondents was small and statistically nonsignificant ($\beta = -0.023$, $p = 0.811$). The reported interaction coefficient was -0.312 ($p = 0.002$). These estimates indicate an apparent subgroup difference within the surveyed sample; they do not establish that female consumers generally dislike AI-based service or that their attachment is unaffected in every retail setting. The comparison also requires verification of group coding, estimation settings, and measurement comparability. Measurement-invariance assessment is relevant before interpreting differences between composite-model coefficients as substantive group differences [15].

One cautious interpretation is that the association between perceived service quality and attachment varies across respondent groups in this particular sample. The difference could reflect distinct service histories, prior AI exposure, brand usage, digital literacy, or unmeasured contextual factors. The study did not experimentally identify empathy preferences or cognitive processing mechanisms by gender. Its findings therefore do not justify treating efficiency as an intrinsically male preference or interpersonal warmth as an intrinsically female preference; preference-sensitive service design is a more defensible implication.

The reported age-group estimates are presented in Table 5.

Table 5. *Reported AI service-quality associations by age group*

Age group	n	ASQ → EBA (β)	ASQ → BL (β)	Service preference
18-25	123	0.312	0.521	AI-favourable
26-35	179	0.294	0.518	AI-favourable
36-45	113	0.201	0.429	Mixed
46-55	61	0.087	0.345	Mixed/Human-leaning
55+	36	-0.089	0.267	Human-favourable

Note: Age categories and preference labels are retained as reported. The 46–55 and 55+ categories overlap at age 55 and require correction from the original coding. Preference labels have no documented separate measurement or classification procedure. No age-group standard errors or comparison tests are supplied.

The subgroup coefficients in Table 5 display a descending numerical pattern across the five age categories. The service-quality–attachment coefficient ranges from 0.312 for respondents aged 18–25 years to -0.089 for the oldest category,

labelled 55 years and above. Service-quality–loyalty coefficients remain positive in all displayed groups. These estimates alone do not establish a statistically significant age interaction, because standard errors, confidence intervals, and pairwise or omnibus comparison tests are absent. The significance of the oldest group's negative coefficient cannot be verified from the available table. Moreover, the overlapping age boundaries must be reconciled with the original coding before the categories are interpreted as mutually exclusive groups.

4.5. MODEL FIT AND PREDICTIVE RELEVANCE

The reported model-evaluation results appear in Table 6.

Table 6. *Reported model-fit statistics and predictive relevance*

Metric	Value	Threshold	Reported interpretation
SRMR	0.084	<0.10	✓ Adequate
GoF	0.456	>0.25	✓ Good
R^2 (Brand loyalty)	0.512	Ideally >0.50	✓ Strong
R^2 (Emotional attachment)	0.035	—	Weak
Q^2 (Predictive Relevance)	0.289	>0	✓ Confirmed
RMSEA	0.062	<0.08	✓ Good

Note: Values, thresholds, and interpretive labels reproduce the reported summary. The GoF label does not establish PLS model validity; R^2 has no universal adequacy threshold; the source of Q^2 and RMSEA remains unverified. These limitations govern interpretation of the table.

The model-assessment statistics reported in Table 6 include SRMR $= 0.084$, a GoF index of 0.456, $R^2 = 0.512$ for brand loyalty, $R^2 = 0.035$ for emotional attachment, $Q^2 = 0.289$, and RMSEA $= 0.062$. The loyalty R^2 is described as indicating that the predictors account for 51.2% of the reported variance, while the attachment R^2 is equivalent to $0.187^2 \approx 0.035$. However, the attachment correlation in Table 2 is 0.412, which would imply $R^2 \approx 0.170$ for a single-predictor standardised model. This inconsistency must be resolved from the original output. In addition, a positive Q^2 value indicates predictive relevance under the chosen procedure but does not alone validate all substantive interpretations.

5. DISCUSSION

5.1. THE PROPOSED MECHANICAL EFFICIENCY PARADOX: INTERPRETATION AND IMPLICATIONS

This investigation raises, rather than conclusively validates, the proposed "mechanical efficiency paradox": strong associations between AI service quality and brand loyalty could coexist with a weaker association between AI service quality and emotional brand attachment. The reported coefficients are positive for both outcomes, so the data presented here do not demonstrate that AI service decreases attachment. The argument should be understood as a possible relative difference between functional and relational pathways. Furthermore, without a human-service comparison group, objective performance records, or longitudinal measures, the study cannot isolate whether automation itself caused improvements in convenience or reductions in emotional connection.

The proposed theoretical mechanism distinguishes functional evaluations of service from the emotional bond with a brand. Convenience, responsiveness, and reliability may influence loyalty intentions, while relational factors such as trust, recognition, and perceived empathy may contribute to attachment. The mechanisms can interact rather than exclude each other, and well-designed AI service may support positive experiences when integrated with accountable human assistance. Consumers may nonetheless experience automated interactions as impersonal in some circumstances. The hypothesis is thus context-dependent and should not be presented as proof of an inherent or universal emotional deficit in all AI systems.

Retailer-level satisfaction scores, customer lifetime value, and repeat-purchase records would offer useful external evidence for evaluating whether the proposed distinction between efficiency and attachment has practical importance. Such measures require verifiable corporate reports or documented administrative datasets, together with clear collection periods and outcome definitions. Without these records, the survey cannot substantiate changes in customer value or retention for Noon, Jarir, or any other participating organisation. If administrative information becomes available, it should be linked to the relevant service encounter and analysed separately from questionnaire responses. Until then, the managerial discussion identifies plausible concerns for investigation rather than confirmed longitudinal trends across Saudi retailers.

5.2. GENDER-GROUP COMPARISONS AND IMPLICATIONS FOR SERVICE DESIGN

The reported subgroup estimates ($\beta = 0.289$ among men and $\beta = -0.023$ among women) suggest variation in the association between service quality and emotional attachment within the surveyed sample. The female subgroup estimate

is statistically indistinguishable from zero, and the estimates should not be described as proving opposite emotional responses to AI. Differences may arise from the brands and service encounters experienced, technology familiarity, age, perceived usefulness, or other factors that were not fully examined. Interpretation should focus on the observed conditional association rather than on assumed universal psychological differences between men and women.

A possible psychological explanation concerns variation in what individual customers value during a service encounter. Some consumers may prioritise efficient resolution, while others may emphasise clarity, reassurance, cultural appropriateness, or personal contact. The data do not establish that such priorities are determined by gender, nor do they measure an experimentally isolated preference for efficiency or emotional reciprocity. Consequently, these explanations remain hypotheses that should be tested using direct preference measures and appropriate adjustments for other demographic characteristics.

A more defensible strategic implication is that retailers should offer service-channel choices based on expressed preferences, accessibility requirements, task complexity, and previous interactions. Rather than automatically assigning an efficiency-focused interface to men and a relationship-focused interface to women, retailers can allow all customers to select prompt automated assistance or support from a trained human agent. Such customer-led personalisation avoids unwarranted demographic assumptions while preserving the possibility of testing whether particular communication styles perform differently across groups.

5.3. AGE-GROUP PATTERNS AND PREFERRED SERVICE CHANNELS

The age-specific estimates in Table 5 show more positive service-quality associations in the younger groups and smaller estimates in the older groups. This pattern may reflect differences in accumulated experience with digital platforms, confidence in automated systems, accessibility, brand choice, or shopping routines. The age-group estimates alone do not establish causal generational mechanisms, and they should not be used to infer that older consumers categorically regard AI as a replacement threat. Proper tests of between-group differences are necessary before the moderation hypothesis can be considered confirmed.

The oldest age group has a reported service-quality–attachment coefficient of -0.089, but Table 5 provides no confidence interval or standard error for that estimate. Its statistical significance therefore cannot be confirmed from the available evidence. A small negative point estimate does not, by itself, demonstrate customer frustration, alienation, or declining loyalty. In addition, the oldest group is labelled 55 years and above, while the preceding group includes age 55. The age-55 observations must be assigned consistently to one mutually exclusive category before the subgroup comparison can be reproduced. Broader age-based claims should also use the same definitions as the analysed groups.

Retailers should provide a visible and usable choice between AI-enabled and human assistance instead of imposing a single mandatory service channel. Such choice can accommodate customers of all ages, including people with accessibility needs, unfamiliarity with a particular interface, or a preference for direct personal assistance. For example, a service screen might ask whether the customer prefers an instant automated response or a human adviser. The effectiveness of this approach should be evaluated with customer feedback and behavioural data rather than assumed solely from age categories.

5.4. PRACTICAL RECOMMENDATIONS FOR SAUDI RETAIL IMPLEMENTATION

Strategy 1: Hybrid Service Architecture. Retailers can establish a coordinated service model with two complementary routes. The AI-enabled route can handle routine information requests, order tracking, product discovery, and other tasks for which speed and availability are priorities. The human route can support unusual cases, unresolved problems, emotionally sensitive complaints, and situations requiring judgment or personalised reassurance. Clear escalation procedures are necessary so that consumers can move smoothly between these channels without losing context or repeating information unnecessarily.

Strategy 2: Preference-Sensitive Personalisation. Retailers can customise service communication according to preferences that customers actually express, such as short factual answers, detailed explanations, interactive guidance, or direct human support. The manuscript's reported gender differences may motivate further segmentation research, but they do not justify automatic gender-based interface assignment. A customer-led model is also better suited to examining whether particular combinations of efficiency, transparency, empathy, and reassurance improve outcomes across different service encounters.

Strategy 3: Accessible Service-Channel Choice. AI and human options should remain available across age groups, with accessible design, clear guidance, straightforward navigation, and a simple route to a person when required. Older and younger customers may differ on average in experience with certain technologies, but age should not be the sole determinant of service assignment. Retailers can instead use opt-in settings, observed usability problems, and direct feedback to tailor support without restricting customers to a predetermined channel.

Strategy 4: Relationship-Building Initiatives. Retailers can complement efficient automated service with loyalty pro-

grammes, human follow-up where appropriate, thoughtful complaint resolution, community-oriented communication, and clear recognition of customer concerns. High-value or high-complexity customers may particularly appreciate reliable access to experienced employees, regardless of their demographic group. Such initiatives should be evaluated using customer satisfaction, retention, complaint resolution, and longitudinal measures of attachment rather than relying exclusively on immediate post-interaction survey responses.

Strategy 5: Organisational Change Management. AI deployment should be framed as a means of supporting service quality and staff effectiveness rather than as a universal substitute for interpersonal service. Employee training should cover escalation, responsible use of AI-generated recommendations, respectful communication, privacy, and cultural sensitivity. Managers should also monitor whether efficiency gains are accompanied by satisfactory outcomes for customers who need additional assistance. This coordinated approach offers a way to manage automated capability and human relationship-building as complementary organisational resources.

5.5. LIMITATIONS AND BOUNDARY CONDITIONS

Sample Characteristics: The reported respondents were concentrated in urban areas, with Riyadh accounting for approximately 56.1%, Jeddah 30.5%, and Dammam 13.5% of the total sample. This limits the direct applicability of the conclusions to rural communities and less digitally connected groups. The educational profile was also concentrated among degree holders, potentially restricting generalisability to consumers with different educational backgrounds. The reported gender distribution was 58% male and 42% female; it should not be presented as representative of Saudi Arabia without appropriate population and sampling evidence.

Temporal Specificity: The reported collection period of May–September 2026 captures responses at one point in a rapidly changing market. Consumers' expectations of automated services could change with further technology adoption, greater familiarity, and modifications to retail platforms. Longitudinal research would be required to establish whether attachment and loyalty evolve as customers acquire additional AI-service experience, and whether apparent differences between age groups persist when prior experience is taken into account.

Causality Constraints: The cross-sectional survey design prevents confident causal inference. Although the conceptual model proposes links from service quality to attachment and loyalty, the collected responses do not establish temporal precedence or eliminate reverse causality and confounding. Randomised service experiments, comparisons between human and AI channels, and repeated observations over time would strengthen inferences about the consequences of automation. In particular, the present design does not independently identify a decrease in emotional attachment caused by AI interaction.

Measurement Limitations: All principal constructs were measured through consumer self-report rather than objective records of service speed, accuracy, or subsequent purchasing behaviour. This raises the possibility of common-method variance, social desirability effects, and shared response tendencies. Objective indicators such as actual response times, repeat purchases, customer lifetime value, customer retention, and complaint-resolution rates would improve validation. The survey also did not include a documented human-service comparison group. In addition, the inconsistency between the interconstruct correlation matrix and the reported structural coefficients requires reanalysis before the results can be considered publication-ready.

The proposed mediation model contains one intervening construct. Its indirect association is therefore the product of the service-quality–attachment path and the attachment–loyalty path, while the total association is the sum of the direct and indirect components when all estimates use a compatible coefficient scale. This decomposition should be reproduced from a single analysis, with the same observations, variable definitions, and model specification. It is not sufficient to combine a correlation from one output with a path coefficient from another. Nor should coefficients estimated on different scales be compared directly to infer which psychological process is stronger.

The questionnaire also requires careful construct-level interpretation. Attachment item EBA7 refers to an inability to imagine switching retailers, while the loyalty items include continued purchasing and resistance to switching. This overlap warrants scrutiny of content validity and empirical distinctiveness. The alternative wording supplied for BL5 must be reconciled with the administered questionnaire, because reverse scoring depends on the actual item and response coding. These are reporting requirements rather than additional analyses claimed to have been performed. The demographic findings likewise remain restricted to the displayed gender and age estimates; no moderation results for digital literacy or prior AI experience are supplied.

Finally, the service-preference labels accompanying the age-group estimates are descriptive classifications in the supplied results. No separate preference scale, classification rule, or inferential test is documented. Those labels therefore cannot establish that a group prefers AI-only or human-only assistance. A reproducible preference analysis would specify the question asked, the response options, the decision rule, and the uncertainty associated with each comparison. Clarifying these distinctions is necessary before moving from statistical associations to operational decisions about service-channel assignment.

6. CONCLUSION AND FUTURE RESEARCH

This manuscript examines associations among perceived AI service quality, emotional brand attachment, and brand loyalty in a reported sample of 512 retail consumers from Saudi Arabia. The supplied coefficients suggest positive associations between AI service quality and loyalty and between AI service quality and attachment, with differences across the displayed demographic subgroups. They do not establish a negative overall effect of AI service on emotional attachment. Although the manuscript reports that the model explains 51.2% of brand-loyalty variance, inconsistencies across its correlations, coefficients, and mediation estimates prevent independent confirmation of that result without the source analysis. The proposed "mechanical efficiency paradox" should therefore remain a hypothesis about the potentially different roles of functional quality and emotional connection rather than a conclusively demonstrated causal mechanism.

For Saudi retailers considering investment in automated service infrastructure, the immediate managerial implication is to integrate effective digital assistance with reliable access to human support. Hybrid AI–human service, preference-sensitive design, accessible channels, and meaningful escalation procedures are plausible approaches to coordinating technological capability and relationship management. Their effectiveness should be tested using clearly defined service encounters and outcomes, rather than inferred from unverified investment totals or assumed demographic preferences. Any segmentation strategy should respond to customers' demonstrated needs and tested service outcomes. Such an approach provides a practical basis for evaluating whether improvements in convenience coexist with the emotional connection required for sustained brand loyalty.

Future research should examine: (1) how specific AI capabilities, including transparency, cultural personalisation, conversational quality, and the appropriate use of empathetic language, relate to emotional attachment; (2) longitudinal changes in consumer responses as AI systems and service expectations evolve; (3) organisational factors, including implementation strategy, employee training, and brand positioning, that could moderate customer outcomes; (4) replications in other Saudi regions and comparable Middle Eastern retail markets; (5) objective behavioural measures beyond stated loyalty intentions, including actual retention and customer lifetime value; and (6) direct experimental comparisons of AI-only, human-only, and hybrid service options.

Competing Interests

The author declares no competing interests related to this study.

Funding

The author received no specific financial support, research grant, or external funding for the research, authorship, or publication of this manuscript.

Data Availability

The data supporting this study are available from the author.

REFERENCES

[1] Communications, Space and Technology Commission (CST). (2026). *Saudi Internet 2025: Usage and digital infrastructure*. https://www.cst.gov.sa/en/knowledge-center/reports/saudi-internet-25. Accessed 1 November 2026.

[2] Kirk, C. P., & Givi, J. (2025). The AI-authorship effect: Understanding authenticity, moral disgust, and consumer responses to AI-generated marketing communications. *Journal of Business Research, 186*, Article 114984. https://doi.org/10.1016/j.jbusres.2024.114984.

[3] Sheng, M. L., Natalia, N., & Rusfian, E. Z. (2025). AI chatbot, human, and in-between: Examining the broader spectrum of technology–human interactions in driving customer–brand relationships across experience and credence services. *Psychology & Marketing, 42*(4), 1051–1071. https://doi.org/10.1002/mar.22165.

[4] Parasuraman, A., Zeithaml, V. A., & Berry, L. L. (1988). SERVQUAL: A multiple-item scale for measuring consumer perceptions of service quality. *Journal of Retailing, 64*(1), 12–40.

[5] Brady, M. K., & Cronin, J. J., Jr. (2001). Some new thoughts on conceptualizing perceived service quality: A hierarchical approach. *Journal of Marketing, 65*(3), 34–49. https://doi.org/10.1509/jmkg.65.3.34.18334.

[6] Zeithaml, V. A., Parasuraman, A., & Malhotra, A. (2002). Service quality delivery through web sites: A critical review of extant knowledge. *Journal of the Academy of Marketing Science, 30*(4), 362–375. https://doi.org/10.1177/009207002236911.

[7] Thomson, M., MacInnis, D. J., & Park, C. W. (2005). The ties that bind: Measuring the strength of consumers' emotional attachments to brands. *Journal of Consumer Psychology, 15*(1), 77–91. https://doi.org/10.1207/s15327663jcp1501_10.

[8] Park, C. W., MacInnis, D. J., Priester, J., Eisingerich, A. B., & Iacobucci, D. (2010). Brand attachment and brand attitude strength: Conceptual and empirical differentiation of two critical brand equity drivers. *Journal of Marketing, 74*(6), 1–17. https://doi.org/10.1509/jmkg.74.6.1.

[9] Bauer, H. H., Grether, M., & Leach, M. (2002). Building customer relations over the Internet. *Industrial Marketing Management, 31*(2), 155–163. https://doi.org/10.1016/S0019-8501(01)00186-9.

[10] Williams, K. C., & Spiro, R. L. (1985). Communication style in the salesperson–customer dyad. *Journal of Marketing Research, 22*(4), 434–442. https://doi.org/10.1177/002224378502200408.

[11] Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39–50. https://doi.org/10.1177/002224378101800104.

[12] Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science, 43*(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8.

[13] Henseler, J., & Sarstedt, M. (2013). Goodness-of-fit indices for partial least squares path modeling. *Computational Statistics, 28*(2), 565–580. https://doi.org/10.1007/s00180-012-0317-1.

[14] SmartPLS. (n.d.). *Blindfolding and Stone–Geisser's Q^2 in PLS-SEM*. SmartPLS Documentation. https://smartpls.com/documentation/algorithms-and-techniques/resampling-and-inference/blindfolding/. Accessed 1 November 2026.

[15] Henseler, J., Ringle, C. M., & Sarstedt, M. (2016). Testing measurement invariance of composites using partial least squares. *International Marketing Review, 33*(3), 405–431. https://doi.org/10.1108/IMR-09-2014-0304.