



Hotel Brand Loyalty in Western Thailand: A Dual-Analytical Approach Using Structural Equation Modeling and Necessary Condition Analysis

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Abstract

This study investigates the relationships among overall service quality, customer satisfaction, customer engagement behaviors, and hotel brand loyalty within the sustainable tourism context of Western Thailand's accommodation sector. It further explores the roles of online reviews, hotel management responses, and artificial intelligence technology in shaping customer perceptions. Data were collected from 459 Thai consumers with prior hotel booking experience through online platforms using a structured questionnaire. Structural equation modeling (SEM) was employed to examine sufficiency relationships among the latent constructs, while necessary condition analysis (NCA) was used to identify minimum threshold conditions for achieving high brand loyalty. The results reveal that the consumer decision-making process and guest online feedback significantly influence perceived service quality, which in turn drives customer satisfaction and engagement behaviors, ultimately leading to brand loyalty. NCA results further demonstrate that service quality and customer satisfaction function as necessary conditions for high loyalty levels, while artificial intelligence showed no statistically significant effect within this context. These findings contribute to the hospitality literature by integrating SEM and NCA to distinguish between sufficiency and necessity conditions, offering actionable insights for improving service quality and fostering long-term brand loyalty in Thai hotels.

Keywords: 1) service quality 2) customer satisfaction 3) customer engagement behaviors 4) brand loyalty 5) artificial intelligence

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Introduction

The tourism and hospitality accommodation sector represents a cornerstone of global economic development, with service quality and customer satisfaction as enduring research priorities (Ali, et al., 2021, p. 21; Nyagadza, et al., 2022, p. 2). Contemporary business environments require accommodation providers to transcend conventional service delivery by cultivating memorable experiences and facilitating customer engagement across digital platforms (Chen, et al., 2021, p. 871; Sitaram and Purohit, 2025, p. 188). Thailand's tourism industry functions as a primary economic catalyst, receiving over 29 million international arrivals during the first ten months of 2024 and yielding revenues exceeding one trillion baht (Ministry of Tourism and Sports, 2024). The western region, encompassing Kanchanaburi and Prachuap Khiri Khan provinces, attracted 3.677 million (5.28%) and 2.794 million (4.01%) visitors respectively in 2024. The region's diverse attractions underscore the imperative for enhanced accommodation service quality.

Overall service quality (OSQ) remains fundamental to customer satisfaction and competitive advantage. The Service Quality (SERVQUAL) framework comprising reliability, responsiveness, assurance, empathy, and tangibles continues as a foundational assessment instrument (Nyagadza, et al., 2022, p. 42; Parasuraman, et al., 1988, p. 12). Ali, et al. (2021, p. 14) demonstrated positive associations between most dimensions and satisfaction, particularly empathy, responsiveness, assurance, and tangibles, though reliability shows

contextual variability. Heterogeneous findings across settings reinforce the necessity for context-specific investigations.

In digitally mediated environments, overall customer satisfaction (OCS) extends beyond service quality to encompass memorable tourism experiences and online review exposure (Feng, et al., 2024, p. 303; Kim (2017, p. 856) established memorable experiences as the strongest predictor of behavioral intentions, mediated through destination image and satisfaction. Zhang, et al. (2018, p. 326) demonstrated that memorable experiences surpass satisfaction in predicting emotional attachment and word-of-mouth. Pujiastuti, et al. (2025, p. 4504) confirmed service quality's direct influence on recommendation intentions, with satisfaction and memorable experiences as critical mediators.

Customer engagement behaviors (CEB) constitute a central construct for understanding non-transactional actions including word-of-mouth, online reviews, and social media interactions (Chen, et al., 2021, p. 871). Sitaram and Purohit (2025, p. 118) found that hotel social media engagement enhances brand attachment and booking intentions, with experience-oriented communications generating superior outcomes. Chen, et al. (2021, p. 871) demonstrated that engagement across five dimensions identification, enthusiasm, attention, absorption, and interaction positively influences behavioral intentions through brand trust mediation. Gli, et al. (2025, p. 379) emphasized online review management and managerial responses as pivotal for fostering satisfaction, engagement, and loyalty. Hotel brand loyalty in



sustainable tourism contexts (HBST) represents a strategic imperative. Gli, et al. (2025, p. 379) revealed that perceived sustainability practices across environmental, economic, and social dimensions positively affect loyalty and revisit intentions. Ali et al. (2021, p. 14) and Tran (2025, p. 3825) corroborated positive effects of green practices on brand loyalty through green hotel image mediation. Notably, 94% of Thai tourists express willingness to pay premiums for environmentally responsible lodging (Rita, Vong and Santos, (2025). Artificial intelligence (AI) technologies increasingly enhance service quality and customer experiences. Evidence from Thailand's western coastal chain hotels indicates AI-driven service attributes influence satisfaction and loyalty, with service efficiency mediating relationships between AI features and loyalty (Prentice, Wang and Loureiro, 2019, p. 50). Altuntas, et al. (2022, p. 846) adapted SERVQUAL for robot service quality evaluation, proposing five dimensions reliability, assurance, entertainment, human-likeness, and tangibles driving continued usage intentions.

Despite substantial global research on service quality, satisfaction, engagement, and loyalty in accommodation contexts, significant gaps remain. First, most studies have been conducted in Western or East Asian contexts, leaving a contextual absence in the Western Thailand hospitality sector, a high-potential region experiencing sustained growth. Second, existing research tends to examine these constructs in isolation, with limited integrated analyses that simultaneously incorporate AI technologies and online review management. Third, methodologically, prior studies have

relied predominantly on regression based approaches without distinguishing between sufficiency and necessity conditions. To address these gaps, this study makes three key contributions: (1) it provides empirical evidence from an underexplored geographic context (2) it integrates multiple constructs including AI and online reviews within a unified framework and (3) it introduces a dual-analytical approach combining Structural Equation Modeling (SEM) and Necessary Condition Analysis (NCA). Specifically, this study investigates the relationships among overall service quality, customer satisfaction, engagement behaviors, and hotel brand loyalty within sustainable tourism contexts in western Thailand's accommodation sector, exploring influences of online reviews, managerial responses, and AI adoption. Employing structural equation modeling (SEM) and necessary condition analysis (NCA), this research addresses knowledge gaps, provides empirical insights, and offers actionable management recommendations aligned with digital transformation and sustainability imperatives. The study employs a cross sectional quantitative design with data collected Thai consumers. SEM is used to examine sufficiency relationships among the latent constructs, while NCA identifies the minimum necessary conditions for achieving green

Literature Review

Guest Online Feedback and Perceived Service Quality

Guest online feedback (GOF) has emerged as a pivotal information source influencing consumers' service quality perceptions

in hospitality. Demonstrated that service quality assessments from online reviews significantly predict customer satisfaction, with review content serving as a proxy for actual experiences. User-generated content is perceived as more reliable than marketer-controlled information, playing a crucial role in shaping consumer trust. However, fraudulent reviews drive increased consumer distrust and threaten review platform integrity (Ahmad and Sun, 2018, p. 77).

Online feedback dimensions extend beyond numerical ratings. Analyzing 37,221 reviews, Korfiatis, García-Bariocanal and Sánchez-Alonso (2012, p. 205) found that readability and comprehensibility significantly affect perceived usefulness. Liu and Park (2015, p. 140) revealed that source characteristics (reviewer expertise, trustworthiness) and message characteristics (argument quality, review length) collectively determine review helpfulness. Radojevic, Stanisic and Stanic (2017, p. 134) established that subjective service aspects value for money, sleep quality, and overall service emerge as key determinants of reviewer satisfaction and feedback valence. Negative feedback can function as customer retaliatory behavior following unsatisfactory experiences, inflicting considerable reputational damage.

Hotel Management Response Strategies

Hotel management responses (HMR) to online reviews represent a critical yet underutilized reputation management tool. Li, et al. (2017, p. 293) indicated that response frequency, timeliness, and content quality jointly influence consumers' perceptions of a hotel's service recovery commitment. Sparks,

So and Bradley (2016, p. 74) demonstrated that managerial responses mitigate negative interpretation of critical reviews, with prompt and substantive replies signaling organizational responsiveness and customer-centric orientation.

Effective managerial responses are rooted in impression management theory and service recovery principles. Public responses transform potentially damaging negative reviews into opportunities demonstrating care for both original reviewers and prospective guests. However, response efficacy varies considerably depending on context and execution; generic or defensive replies may exacerbate reputational harm. Despite strategic importance, managerial responses exhibit weaker direct effects on booking intentions compared to review content itself, underscoring that genuine service quality improvements remain more influential than reactive communication strategies.

Consumer Decision-Making Process and Selection Behavior

The consumer decision making process (DMP) in hotel selection has undergone fundamental restructuring due to online review availability. Chan, et al. (2017, p. 54) revealed that review valence significantly influences booking intentions, moderated by demographic similarity between readers and reviewers. Casalóa, et al. (2015, p. 49) demonstrated that ratings on reputable platforms such as TripAdvisor are perceived as more useful and trustworthy, engendering higher booking intentions. Online reviews fulfill distinct functions across cognitive stages. During information search,



reviews provide detailed experiential insights unavailable through official channels (Ukpabi and Karjaluo, 2016, p. 618). In alternative evaluation, aggregate ratings serve as quality heuristics simplifying comparisons (Lee, Hu and Lu, 2018, p. 436). Chan, et al. (2017, p. 54) reported that 95% of travelers consult online reviews prior to booking, with positive reviews exerting pronounced impact on decisions. This influence extends to emotional responses and trust formation, mediating booking intentions (Gavilan, et al., 2018, p. 53). These dynamics illustrate how online reviews have transformed traditional decision-making models by introducing user-generated content as a primary informational and persuasive element.

Overall Service Quality and Customer Satisfaction

Overall service quality (OSQ) remains the cornerstone of hospitality excellence, with online reviews functioning as collective quality assessment mechanisms. High perceived quality stimulates positive reviews, creating a reinforcing feedback loop Chan, et al. (2021, p. 871) found that 1% rating increases correlate with 2.68% sales rises per available room. Consumers rely on star ratings as screening tools, though subjective assessments of value, sleep quality, and service often outweigh official ratings in driving satisfaction (Radojevic, Stanistic and Stanic, 2017, p. 134). Overall customer satisfaction (OCS) mediates between perceived quality and behavioral outcomes. Satisfaction operates dually: from service experiences (motivating reviews) and from reading reviews (influencing bookings). Luo and Qu (2016, p. 311) established that perceived quality significantly

affects loyalty and revisit intentions through satisfaction mediation. Berezina, et al. (2015, p. 1) noted that when positive reviews elevate expectations, service falling short yields disproportionate dissatisfaction. Satisfied customers influenced by reviews continue depending on them for decisions and respond favorably to managerial responses (Li, et al., 2017, p. 5). This underscores reciprocal relationships between service delivery, satisfaction, and digital review ecosystems.

Customer Engagement Behaviors and Brand Loyalty

Customer engagement behaviors (CEB) extend beyond transactions to include reviews, recommendations, and advocacy. Service quality predicts behavioral intentions, with satisfied customers generating positive reviews and dissatisfied ones switching providers. Engagement behaviors enhance loyalty (Rather and Sharma, 2017, p. 1; Rasoolimanesh, et al., 2019, p. 559), driven by satisfaction or dissatisfaction. Trust, usefulness, and enjoyment influence repurchase intentions, while price dissatisfaction prompts switching (Keaveney, 1995, p. 71). Hotel brand loyalty linked to sustainable tourism (HBST) depends on service experiences and engagement. Li, Teng and Chen (2020, p. 184) confirmed CEB as a key loyalty determinant in social media contexts. Customers pay premiums based on ratings, with booking intentions tied to satisfaction (Martin-Fuentes, 2016, p. 126). Electronic service quality affects satisfaction, which influences engagement and loyalty (Vo, et al., 2019, p. 499). This research demonstrates the pathway from service quality through satisfaction and

engagement to loyalty, emphasizing digital interactions' role in hospitality.

Artificial Intelligence in Hospitality

Decision-Making

The integration of artificial intelligence (AI) into the hospitality industry marks a pivotal advancement that is reshaping customer interactions and decision-making processes. AI applications in hotels range from real time chatbots for customer service to advanced recommendation systems that analyze user preferences and review patterns. Although prior research has primarily emphasized human generated reviews and human-managed responses, AI is increasingly acting as an intermediary in these exchanges, potentially affecting perceptions of review authenticity and the efficacy of managerial responses. The convergence of AI adoption with traditional service quality dimensions, customer satisfaction, and engagement behaviors merits systematic examination to understand how technological augmentation modifies established relational pathways in hospitality contexts. In essence, AI serves as a mediating force in the digital hospitality ecosystem, bridging conventional human centric interactions with automated efficiencies. This intersection not only amplifies operational capabilities but also introduces complexities regarding trust and genuineness, underscoring the need for balanced human-AI hybrid models to sustain customer-centric outcomes in an evolving industry landscape. Recent studies have further explored AI applications in tourism contexts. Tussyadiah (2020,p.5) demonstrated that AI-powered chatbots significantly improve response time and customer

satisfaction in hotel booking processes. Pillai and Sivathanu (2020, p. 3199) found that perceived usefulness and anthropomorphism of AI concierges positively influence adoption intentions among hotel guests. Li, et al. (2020, p. 184) examined the impact of AI-based recommendation systems on tourist decision-making, revealing that algorithmic suggestions enhance perceived personalization but may reduce trust when customers perceive lack of human oversight. These findings collectively suggest that while AI holds considerable promise for the hospitality industry, its effectiveness depends heavily on implementation context, customer familiarity, and the balance between automation and human interaction.

The foregoing literature review reveals several critical gaps warranting further investigation. First, while extensive research has examined service quality, customer satisfaction, engagement behaviors, and brand loyalty independently, few studies have simultaneously integrated these constructs with online review management and AI technology within a single analytical framework. Second, the majority of empirical evidence originates from Western or East Asian hospitality contexts, leaving a notable contextual absence in the Southeast Asian market, particularly in Thailand's western region, which represents a high-growth tourism corridor with distinctive service characteristics. Third, from a methodological standpoint, prior studies have relied predominantly on regression-based or conventional SEM approaches that assess sufficiency conditions, without distinguishing whether certain factors constitute necessary preconditions



for desired outcomes. The emerging Necessary Condition Analysis (NCA) methodology addresses this limitation by identifying minimum threshold requirements that must be satisfied before an outcome can be achieved (Dul, 2016, p. 10), yet its application in hospitality research remains scarce. These gaps collectively motivate the present study, which seeks to provide an integrated empirical examination of the relationships among service quality, satisfaction, engagement, and loyalty within the sustainable tourism context of Western Thailand, employing a dual-analytical approach combining SEM and NCA to offer both sufficiency and necessity perspectives.

Accordingly, this study tests eight hypotheses within the integrated framework.

Guest Online Feedback (H1), Hotel Management Response (H2), and Decision-Making Process (H3) are each hypothesised to exert a positive and significant effect on Overall Service Quality (OSQ). Overall Service Quality in turn is expected to positively influence both Overall Customer Satisfaction (H4) and Customer Engagement Behaviors (H5), while Overall Customer Satisfaction also positively affects Customer Engagement Behaviors (H6). Artificial Intelligence application is hypothesised to have a significant effect on Customer Engagement Behaviors (H7), and Customer Engagement Behaviors are expected to positively influence Hotel Brand Stickiness/Sustainable Tourism (H8).

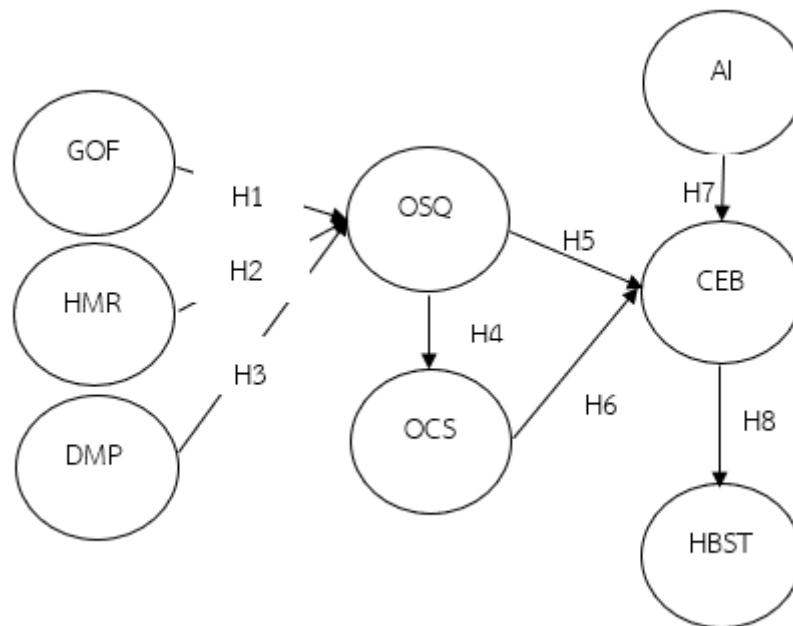


Figure 1 Conceptual Research Framework showing hypothesized sufficiency paths (H1–H8) tested via SEM and necessary conditions tested via NCA. Note. GOF = Guest Online Feedback; HMR = Hotel Management Response; DMP = Decision-Making Process; OSQ = Overall Service Quality; OCS = Overall Customer Satisfaction; CEB = Customer Engagement Behaviors; AI = Artificial Intelligence Application; HBST = Hotel Brand Stickiness / Sustainable Tourism.

Methodology

Research Design and Theoretical Framework

This study employs a cross sectional quantitative research design to investigate the relationships among guest online feedback, service quality, customer satisfaction, engagement behaviors, and hotel brand loyalty within the context of sustainable tourism. The conceptual framework is grounded in an interdisciplinary theoretical foundation and incorporates a research model comprising eight latent variables. The independent variables include Guest Online Feedback (GOF), Hotel Management Response (HMR), and Consumer Decision-Making Process (DMP). The ultimate dependent variable is Hotel Brand Loyalty/Sustainable Tourism (HBST), while the mediating variables consist of Overall Service Quality (OSQ), Overall Customer Satisfaction (OCS), and Customer Engagement Behaviors (CEB). Additionally, Artificial Intelligence Usage (AI) is introduced as an supplementary variable to evaluate the influence of modern technology on the online review ecosystem.

Instrument Development and Variable Operationalization

This study develops an integrative conceptual framework drawing from multidisciplinary theories to assess the influence of online guest feedback and hotel responses on consumer behavior. The measurement structure comprises eight constructs derived from a systematic literature review. Guest Online Feedback (GOF) measures perceived credibility and value of online reviews, adapted from the frameworks of Radojevic, Stanic

and Stanic (2017, p. 134). Hotel Management Response (HMR) evaluates the effectiveness of online complaint management by assessing response frequency, timeliness, and clarity, grounded in service recovery theory. Consumer Decision-Making Process (DMP) captures the utilization of positive reviews and their influence on booking decisions. Overall Service Quality (OSQ) extends the SERVQUAL model, evaluating the linkage between service quality and the generation of positive reviews. Overall Customer Satisfaction (OCS) examines expectation confirmation through comparisons between online reviews and actual experiences. Customer Engagement Behaviors (CEB) assess extra-role behaviors beyond purchase expectations, encompassing both positive actions (e.g., review creation and repurchase) and negative actions (e.g., criticism and service switching). These behaviors ultimately contribute to Hotel Brand Loyalty/Sustainable Tourism (HBST), which measures willingness to pay a premium and the formation of long-term relationships. Finally, Technology Acceptance of AI (TAI) evaluates perceived usefulness and ease of use of AI technologies in automated responses and sentiment analysis. All constructs are operationalized using multi-item scales validated in prior hospitality research, ensuring reliability and validity suitable for structural equation modeling.

Questionnaire Design and Measurement Scales

The questionnaire was developed in Thai and structured into three distinct sections. The first section comprised screening questions to ensure respondent eligibility, confirming that



participants had at least one experience booking accommodation via online platforms within the past year. The second section consisted of 29 items measuring the eight latent constructs, employing a 6 point Likert scale (1 = strongly disagree to 6 = strongly agree). The selection of a 6 point scale, as opposed to the more conventional 5- or 7-point formats, followed the recommendations of Wattanacharoensil, et al. (2024, p. 7), who demonstrated that this configuration enhances measurement sensitivity and discriminant validity without compromising scale reliability. The third section collected demographic information, including gender, age, educational attainment, and patterns of online platform usage. The questionnaire underwent rigorous content validity assessment by three experts in hospitality management and digital marketing to verify item wording appropriateness and theoretical alignment with construct definitions. A pilot test was subsequently conducted with 30 respondents to evaluate comprehension, completion time, and overall clarity. Feedback from the pilot led to minor refinements in phrasing for several items to improve precision and respondent understanding. Content validity was assessed using the Item Objective Congruence (IOC) index evaluated by three subject-matter experts. All items achieved IOC values exceeding 0.67, surpassing the commonly accepted threshold of 0.50 (Rovinelli and Hambleton, 1977, p. 49). Reliability was established through Cronbach's alpha coefficients, which ranged from 0.78 to 0.91 across all constructs, exceeding the recommended minimum of 0.70 (Nunnally and Bernstein, 1994). The selection

of a 6-point Likert scale follows Wattanacharoensil, et al. (2024, p. 7), who demonstrated that even-numbered scales eliminate neutral midpoint responses, thereby reducing central tendency bias and enhancing measurement sensitivity.

Sampling and Data Collection Procedures

The target population comprised Thai consumers with prior experience booking hotels through online platforms a large and geographically dispersed population for which definitive enumeration was not feasible. Sample size determination was therefore guided by the Krejcie and Morgan (1970, p. 607) table and the guidelines of Hair, et al. (2006, p. 54), which recommend a minimum of 384 respondents for populations exceeding one million or of unknown size at a 95% confidence level and $\pm 5\%$ margin of error. To accommodate potential incomplete responses, data collection targeted 450 usable questionnaires. Data were collected from June 1 to July 31, 2025, using a mixed-mode approach to enhance representativeness and mitigate self-selection bias. A purposive sampling strategy was employed, targeting Thai consumers aged 18 years and above who had booked hotel accommodation through online platforms within the preceding 12 months. The sample size of 459 exceeds the minimum requirement recommended by Hair, et al. (2006, p. 54), who suggest a ratio of at least 10 observations per estimated parameter for SEM analyses. With 29 observed variables in the measurement model, the minimum sample size would be 290, and the obtained sample of 459 provides a ratio of approximately 15.8:1, well above this thresh-

old. Primary distribution occurred through an online questionnaire hosted on Google Forms and disseminated via social media platforms (Facebook, Instagram, LINE), mailing lists, and travel related online forums. Concurrently, paper-based questionnaires were administered in public venues, including shopping malls, transportation hubs, and university campuses. All participants received a clear explanation of the study objectives, their right to withdraw at any stage, and assurances of data confidentiality in accordance with human research ethics standards. The study protocol was approved by the institutional review board under certificate number KUREC-KPS68/054. A total of 459 questionnaires were returned: 412 online (89.8%) and 47 paper-based (10.2%). Following data screening, all responses were deemed complete and free of irregular response patterns, yielding a final usable sample of 459 19.5% above the minimum threshold. This excess ensures sufficient statistical power for detecting hypothesized relationships and supports robust inference in subsequent structural equation modeling and necessary condition analyses. To assess common method bias, Harman's single factor test was conducted. No single factor accounted for more than 35% of the total variance, below the 50% threshold (Podsakoff, et al., 2003, p. 879), suggesting common method bias does not pose a significant threat. The cross-sectional design limits causal inference; relationships identified should be interpreted as associations rather than causal effects (Spector, 2019, p. 125). To assess the robustness of the structural model estimates, bootstrap resampling with 5,000 iterations was employed to derive 95% confidence intervals

for all path coefficients. The stability of the estimates across bootstrap samples provides evidence of robustness. Additionally, the HTMT ratio and Fornell-Larcker criterion were used to confirm discriminant validity, serving as sensitivity checks for the measurement model specification.

Characteristics of the Sample

The sample ($n = 459$) was predominantly female (52.9%), aged 16–35 years (79.3%), and held at least a bachelor's degree (81.3%). The remaining respondents were male (34.6%) or preferred not to specify gender (12.4%), with smaller proportions aged 36–45 (11.3%) and over 45 (9.4%). This demographic profile represents a digitally literate consumer segment with high familiarity with online booking platforms, aligning with the study's focus on the role of online reviews in hotel selection behaviour.

Data Analysis

The present study employed Generalized Structured Component Analysis with Measurement Error (GSCAM), a structural equation modelling technique based on component principles that effectively accommodates measurement error without requiring the assumption of multivariate normality. GSCAM was selected over covariance-based SEM (CB-SEM) and partial least squares SEM (PLS-SEM) for several reasons: (1) GSCAM provides consistent estimates comparable to CB-SEM while maintaining the flexibility of component-based approaches; (2) it accommodates both reflective and formative measurement models; and (3) it does not require the strict distributional assumptions of maximum likelihood estimation, making it suitable for the present data



characteristics (Hwang and Takane, 2014). Evaluation of the measurement model revealed composite reliability coefficients (ρ) for all eight latent variables ranging from 0.757 to 0.878, average variance extracted (AVE) values exceeding 0.50, and standardised factor loadings between 0.63 and 0.95 ($p < 0.001$), thereby confirming adequate reliability and convergent validity. Overall model fit indices were acceptable (Goodness-of-Fit Index [GFI] = 0.965; Standardized Root Mean Square Residual [SRMR] = 0.087). Parameter estimation utilised a bootstrap procedure with 5,000 resamples to derive 95% confidence intervals. Hypothesis testing indicated that the decision-making process (DMP) exerted the strongest influence on online service quality (OSQ), with $\beta = 0.56$ ($p < 0.01$), followed by guest online feedback (GOF) at $\beta = 0.26$ ($p < 0.01$). In contrast, hotel management responses (HMR) and the application of artificial intelligence (AI) exhibited no statistically significant effects. Service quality demonstrated a strong positive effect on customer satisfaction (OCS), with $\beta = 0.76$ ($p < 0.001$), and a moderate effect on customer engagement behaviour (CEB), with $\beta = 0.36$ ($p < 0.05$). Customer satisfaction, in turn, strongly influenced customer engagement behaviour ($\beta = 0.71$, $p < 0.001$), which emerged as the primary determinant of hotel brand stickiness (HBST), with $\beta = 0.78$ ($p < 0.001$). Furthermore, Necessary Condition Analysis (NCA), following Dul's (2016, p.10) approach, revealed that service quality, customer satisfaction, and customer engagement behaviour each displayed effect sizes above the ceiling line exceeding 0.10 and attained statistical significance, thereby constituting necessary conditions for fostering

hotel brand stickiness. These findings complement the linear analysis by affirming that the absence of these necessary factors precludes the attainment of the desired outcome.

Results

Evaluation of the Measurement Model and Structural Hypothesis Testing

The measurement model in this study was evaluated using a composite-based structural equation modelling (SEM) approach implemented through the Generalized Structured Component Analysis with Measurement Error (GSCAM) software. This technique is widely recognised for its ability to provide unbiased estimates in latent factor models, while also generating composite scores suitable for subsequent analyses. A key advantage of this method lies in its avoidance of the inconsistency issues that can arise with maximum likelihood estimators, particularly under conditions of insufficient responses, and its capacity to utilise full information for model estimation.

Assessment of internal consistency revealed that composite reliability coefficients (ρ) for all latent constructs ranged from 0.757 to 0.878, exceeding the recommended threshold of 0.70 and thereby indicating strong internal consistency among the respective indicator sets. Average variance extracted (AVE) values generally surpassed 0.50, with the exception of the Guest Online Feedback (GOF) construct (AVE = 0.45), which fell slightly below the 0.50 threshold. However, GOF was retained based on several justifications: (1) composite reliability exceeded 0.70, indicating adequate internal consistency (Fornell and Larcker, 1981, p.39); (2) all standardized factor loadings were significant and above 0.60; and (3) GOF

represents a theoretically essential construct. Following Hair, et al. (2006, p. 54), constructs with AVE slightly below 0.50 may be retained when composite reliability is satisfactory. Standardised factor loadings ranged from 0.63 to 0.95, with 95% confidence intervals excluding zero, thus confirming reliable convergent validity. Furthermore, discriminant validity was established through the Heterotrait-Monotrait (HTMT) ratio and the Fornell-Larcker criterion, where inter-construct correlations were below 0.85, ensuring that the constructs were sufficiently distinct. Overall model fit for the measurement component was satisfactory, as evidenced by a Goodness-of-Fit Index (GFI) of 0.965 and a Standardized Root Mean Square Residual (SRMR) of 0.087, both aligning with established benchmarks in the literature.

In the structural model evaluation, path analyses revealed varying degrees of significance across hypothesised relationships. Guest online feedback (GOF) exerted a moderate positive effect on perceived overall service quality (OSQ), with a path coefficient of 0.257 (95% CI: 0.127–0.392). In contrast, hotel management responses (HMR) showed no statistically significant influence on OSQ ($\beta = 0.049$; 95% CI: -0.012 – 0.135), suggesting that this factor may not serve as a primary determinant of service quality perceptions. The decision-making process (DMP) emerged as the most influential predictor of OSQ ($\beta = 0.560$; 95% CI: 0.418 – 0.682), underscoring the substantial impact of information and reviews from travel platforms on quality perceptions. Service quality (OSQ) was a strong predictor of overall customer satisfaction (OCS), exhibiting

a coefficient of 0.764 (95% CI: 0.724 – 0.837), and demonstrated a moderate influence on customer engagement behaviour (CEB) ($\beta = 0.361$; 95% CI: 0.090 – 0.553). Concurrently, OCS represented the most potent driver of CEB ($\beta = 0.706$; 95% CI: 0.478 – 0.867), indicating that heightened satisfaction effectively stimulates greater customer engagement with the brand. The application of artificial intelligence (AI) in review management yielded a small negative coefficient that was not statistically distinguishable from zero ($\beta = -0.222$; 95% CI: -0.409 – 0.019), potentially reflecting customers' limited awareness or valuation of AI's role in this context. Customer engagement behaviour (CEB) exerted a strong and significant effect on sustainable hotel/travel brand loyalty (HBST) ($\beta = 0.776$; 95% CI: 0.706 – 0.826), consistent with hypothesis H2 positing engagement behaviour as a precursor to loyalty. Coefficients of determination (R^2) derived from the multiple regression framework indicated that the model accounted for approximately 54.3% of the variance in OSQ, 45.6% in OCS, 53.0% in CEB, and 47.3% in HBST, representing moderate to high explanatory power. In summary, the integration of online review information, hotel responses, service quality, and customer experiences plays a critical role in shaping both attitudinal and behavioural loyalty toward the brand, with the decision-making process and customer satisfaction emerging as particularly salient influences. By contrast, the deployment of AI technologies did not yield statistically significant effects within this contextual framework.

**Table 1** Summary of Path Coefficients from the Structural Model

Relationship	$\hat{\beta}_i$	SE	CI $_{\beta}$	R ²
GOF → OSQ	0.257	0.06	(0.127, 0.392)	0.54
HMR → OSQ	0.049	0.04	(-0.012, 0.135)	0.54
DMP → OSQ	0.56	0.06	(0.418, 0.682)	0.54
OSQ → OCS	0.764	0.03	(0.724, 0.837)	0.46
OSQ → CEB	0.361	0.11	(0.090, 0.553)	0.53
OCS → CEB	0.706	0.1	(0.478, 0.867)	0.53
AI → CEB	-0.222	0.12	(-0.409, 0.019)	0.53
CEB → HBST	0.776	0.03	(0.706, 0.826)	0.47

Note: $\hat{\beta}_i$ denotes the estimated path coefficient; SE is the standard error; CI $_{\beta}$ represents the 95% confidence interval; and R² indicates the coefficient of determination for each endogenous variable. R² for Overall Service Quality (OSQ) derives from regressing OSQ on GOF, HMR, and DMP; for Overall Customer Satisfaction (OCS) on OSQ; for Customer Engagement Behaviour (CEB) on OSQ, OCS, and AI; and for Sustainable Hotel/Travel Brand Stickiness (HBST) on CEB. Overall model fit indices were GFI = 0.965 and SRMR = 0.087, both meeting acceptable criteria.

Results of Necessary Condition Analysis (NCA)

The NCA was conducted in strict accordance with the procedures outlined by Dul (2016, p. 10) and Richter, et al. (2020, p. 2243). Factor scores for each construct, derived from the GSCAM analysis, were utilised as input for the NCA package (version 4.0.2) in R Studio. The initial step involved explicitly defining the condition variables (predictors) and the outcome variable. In this study, seven quality-related constructs were examined as potential necessary conditions for achieving high levels of hotel booking stickiness (HBST): Guest Online Feedback (GOF), Hotel Management Response (HMR), Digital Marketing Process (DMP), Overall Service Quality (OSQ), Overall Customer Satisfaction (OCS), Customer Engagement Behaviour (CEB), and Artificial Intelligence Application (AI).

The NCA results revealed that GOF ($d = 0.210^*$, $p = 0.002$) and OCS ($d = 0.203^*$, $p = 0.016$) exhibited moderate effect sizes, emerg-

ing as the most critical necessary conditions for attaining high HBST scores. These were followed by AI ($d = 0.147^*$, $p = 0.002$), OSQ ($d = 0.125^*$, $p = 0.002$), and HMR ($d = 0.118^*$, $p = 0.002$), all demonstrating small-to-moderate effect sizes and qualifying as necessary conditions. In contrast, DMP ($d = 0.077^*$, $p = 0.020$) and CEB ($d = 0.043^*$, $p = 0.036$) displayed effect sizes below the 0.10 benchmark and were therefore not classified as necessary conditions despite statistical significance. Effect sizes (d) were calculated as the proportion of the area above the ceiling line relative to the total scope, whereby higher d values indicate that low levels of the condition variable preclude the outcome from reaching high levels.

Bottleneck analysis further indicated the minimum levels required for each condition to support HBST at or above the 80th percentile (0.8 on the normalised scale). Specifically, GOF and OCS required minimum levels of at least 40% and 45% of the observed

range (approximately 3.75–4.0 on a 1–6 Likert scale), respectively. HMR, DMP, OSQ, and AI necessitated thresholds of approximately 30–36% (≈ 3.0 – 4.25), whereas CEB required only 11% (≈ 2.8). This suggests that even modestly elevated customer engagement behaviour can sufficiently support high booking stickiness.

These findings lend support to the research hypotheses, demonstrating that insufficient levels of these quality factors par-

ticularly GOF and OCS severely constrain the attainment of high HBST. The results highlight a clear hierarchy of priority for managerial attention, underscoring that enhancing alignment between guest expectations and service delivery, alongside fostering positive online customer experiences, constitutes fundamental and necessary preconditions for maximising customer stickiness in hotel bookings.

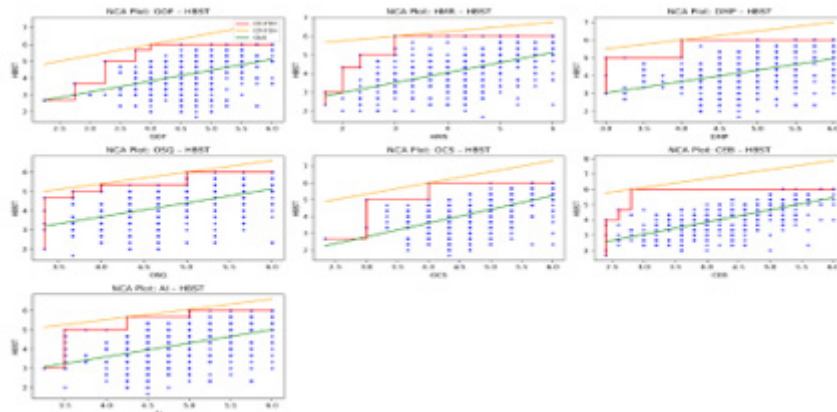


Figure 2 NCA ceiling line plots for seven condition variables predicting HBST. Each panel displays observed data points with the CE-FDH ceiling line. The empty upper-left zone represents the necessity effect; larger empty zones indicate that low levels of the condition preclude high outcome levels.

Joint Analysis of SEM and NCA

The integration of SEM and NCA analyses provides deeper insights into the role of each factor in terms of both necessity and sufficiency conditions. The SEM analysis revealed that GOF, OSQ, and OCS exhibited significantly positive path coefficients toward HBST, whereas DMP and CEB showed minimal or insignificant effects. Meanwhile, AI demonstrated its impact through enhancing service efficiency and online experiences. When compared with NCA results, GOF, OSQ, and OCS were found to be both necessary and sufficient conditions, meaning that without minimum levels of these

variables, high satisfaction cannot be achieved, and when present at high levels, they significantly enhance satisfaction. HMR and AI were identified as necessary but not sufficient conditions in themselves, indicating that they should be employed in conjunction with other factors to generate positive effects on HBST. CEB exhibited the status of a sufficient but not necessary condition, suggesting that even without high customer engagement, satisfaction can still be achieved if other core factors are at adequate levels. Conversely, DMP demonstrated neither necessary nor sufficient properties in this context, as evidenced by both NCA



results and insignificant SEM pathways. Overall, this joint two-method analysis indicates that service quality management (GOF, OSQ, OCS), personnel capability enhancement (HMR), and AI technology implementation are critical in

driving customer satisfaction in hotel bookings, serving both as fundamental conditions that must be present and as sufficient conditions that further strengthen positive experiences.

Table 2 Effect Sizes of Each Variable (NCA effect size) on HBST

Variable (Construct)	CE FDH (d)	p value	Necessary?
GOF (Guest Online Feedback)	0.210*	0.002	Yes
HMR (Hotel Management Response)	0.118*	0.002	Yes
DMP (Decision Making Process)	0.077*	0.02	No
OSQ (Overall Service Quality)	0.125*	0.002	Yes
OCS (Overall Customer Satisfaction)	0.203*	0.016	Yes
CEB (Customer Engagement Behaviors)	0.043*	0.036	No
AI (AI Artificial Intelligence User)	0.147*	0.002	Yes

Note: CE-FDH (d) = Ceiling Envelopment–Free Disposal Hull effect size; p-values obtained via permutation test (10,000 resamples). A construct is classified as a necessary condition when $d \geq 0.10$ and $p < 0.05$. * $p < 0.05$.

In interpreting NCA results, the CE-FDH effect size (d) reflects the proportion of empty space above the ceiling line relative to the total area of the scatter plot, indicating the extent to which a factor constrains the level of outcomes. A higher d value suggests that when that factor is at a low level, the outcome cannot reach higher levels according to necessity theory. Generally, a variable is classified as a necessary condition when $d \geq 0.1$ and the permutation test result (p-value) is below 0.05 to confirm that such empty zones do not occur by chance. The study findings revealed that Guest Online Feedback (GOF), Hotel Management Response (HMR), Overall Service Quality (OSQ), Overall Customer Satisfaction (OCS), and Artificial Intelligence (AI) exhibited d values ranging from 0.12–0.21 with statistical significance, thus qualifying as necessary conditions for hotel brand loyalty and sustainable tourism

(HBST). Meanwhile, DMP and CEB demonstrated d values below the threshold, and despite statistical significance, were not classified as necessary conditions. NCA analysis provides a perspective distinct from linear regression analysis by revealing that certain factors may produce positive effects without reaching high levels, enabling practitioners to prioritize investments or improvements in critical factors to effectively enhance customer satisfaction and loyalty.

Table 3 presents the classification of variables according to necessity and sufficiency conditions to explain the development of hotel brand loyalty/sustainable tourism (HBST) levels in a manner consistent with the example.

Condition	Sufficient*	Insufficient
Necessary	GOF, OSQ, OCS	HMR, AI
Unnecessary	–	DMP, CEB

Note: GOF = Guest Online Feedback, HMR = Hotel Management Response, DMP = Decision-Making Process, OSQ = Overall Service Quality, OCS = Overall Customer Satisfaction, CEB = Customer Engagement Behaviors, AI = Artificial Intelligence User, HBST = Hotel Brand Loyalty and Sustainable Tourism

Discussion

The structural model confirms that OSQ strongly predicts OCS ($\beta = 0.764$, $p < 0.001$), consistent with SERVQUAL theory (Parasuraman, et al., 1988, p. 12; Ali, et al., 2021, p. 14). The NCA extends this finding: when OCS is specified as the outcome variable, OSQ emerges as a necessary condition with a bottleneck threshold at approximately 70% of the observed range roughly 4.2 on the 6-point scale below which satisfaction at the 80th percentile becomes unattainable (Dul, 2016, p. 10). This threshold behavior suggests that service quality operates as a hygiene factor below a critical level, no combination of supplementary factors can compensate for its absence. The theoretical implication is that Expectancy-Disconfirmation processes may not activate meaningfully until a baseline service standard has been met, extending current understanding of satisfaction formation in hospitality contexts.

Among the antecedents of OSQ, DMP emerged as the strongest predictor ($\beta = 0.560$, $p < 0.01$), followed by GOF ($\beta = 0.257$, $p < 0.01$), while HMR showed no significant effect ($\beta = 0.049$, n.s.). This contrasts with Li, et al. (2020, p. 184), who found management responses significantly associated with hotel

performance, and Li, et al. (2017, p. 293), who demonstrated a signaling effect of managerial responses on consumer perceptions. The divergence likely reflects methodological and contextual differences: whereas those studies measured hotel-level performance outcomes using large-scale panel data from major review platforms, the present study measured individual-level quality perceptions among Thai consumers for whom pre-consumption information from online platforms may carry greater weight than post hoc provider responses. This suggests that in digitally mediated markets where peer-generated content dominates, proactive service quality improvement may be more effective than reactive response management.

OCS strongly drives CEB ($\beta = 0.706$, $p < 0.001$), and CEB is the primary determinant of HBST ($\beta = 0.776$, $p < 0.001$), consistent with Customer Engagement theory (Kumar, et al., 2019, p.135). Engagement through co-developing constructive feedback and brand defending exerted stronger influence than general experience sharing. This can be explained through psychological ownership theory, guests who invest cognitive effort in co-creating service improvements develop a sense of ownership



over the brand relationship, transforming transactional satisfaction into relational commitment (Morgan and Hunt, 1994, p. 20). However, the NCA reveals that CEB is sufficient but not necessary for high HBST ($d = 0.043$), indicating that loyalty can emerge without high engagement if foundational factors OSQ, OCS, and GOF are adequately maintained. Engagement thus functions as an accelerator rather than a prerequisite.

AI technology showed no significant linear effect ($\beta = -0.222$) yet NCA classified it as a necessary condition for high HBST ($d = 0.147$, $p < 0.01$). This divergence contrasts with Prentice, Wang and Loureiro (2019, p. 50), who found AI-driven service attributes significantly influencing satisfaction and loyalty in coastal chain hotels. The discrepancy may be explained by the maturity gap: Prentice, Wang and Loureiro (2019, p. 50), examined international chain properties with established AI infrastructure, whereas the present study encompasses a broader range of hotel categories in western Thailand where AI deployment remains nascent. Consequently, many respondents may have had limited direct experience with AI-enabled hotel services, reducing their ability to evaluate AI's contribution to service quality and loyalty. The AI construct was also measured through perceptions rather than actual usage, potentially attenuating the effect. The NCA result suggests that AI operates as an infrastructural necessity its absence constrains loyalty ceilings yet its presence does not linearly enhance outcomes, consistent with Huang and Rust's (2021, p. 30) augmentation perspective. Future research should employ

behavioral AI usage metrics to disentangle awareness from interaction effects.

The joint SEM–NCA classification (Table 3) demonstrates that statistical significance and practical indispensability are distinct properties. GOF, OSQ, and OCS are both necessary and sufficient baseline requirements that also drive incremental gains. HMR and AI are necessary but not sufficient enabling conditions whose SEM paths are non-significant yet whose absence constrains outcomes. CEB is sufficient but not necessary a powerful amplifier that is not a prerequisite. DMP operates exclusively through OSQ and is neither necessary nor sufficient for HBST directly. This fourfold distinction provides a resource allocation logic unavailable from SEM alone: necessary conditions define minimum investment thresholds, while sufficient conditions identify where additional investment yields the greatest marginal returns.

Managerial Implications

In practical terms, the research findings indicate that hotels should (1) maintain service quality at a minimum level of 70% as a fundamental condition, (2) develop systematic strategies to promote CEB, especially co-developing constructive feedback, and (3) invest in AI technology cautiously, focusing on augmenting employee capabilities rather than replacement. Furthermore, linking loyalty with sustainable tourism demonstrates opportunities for differentiation and long-term competitive advantage through integration of sustainability practices. Specifically, hotels adopting environmentally responsible practices can leverage service quality and customer

engagement as pathways to sustainable brand loyalty, contributing to long-term profitability and community well-being in the Western Thailand tourism corridor.

Conclusion

This study integrated Structural Equation Modeling (SEM) and Necessary Condition Analysis (NCA) to examine how online information, service quality, satisfaction, engagement, and AI adoption jointly shape hotel brand loyalty and sustainable tourism outcomes in the western Thailand accommodation sector. The dual-analytical approach revealed a clear power shift in quality perception from service providers to online consumer communities: customer decision-making processes and guest online feedback significantly predicted service quality, whereas hotel management response did not. Service quality in turn functioned as a threshold condition for satisfaction, and engagement behaviours particularly co-developing constructive feedback and brand defending emerged as the strongest pathway to loyalty, consistent with Customer Engagement theory (Rita, Vong and Santos, 2025). The divergence between AI's non-significant linear effect and its necessary-condition status reflects the Service Automation Paradox, whereby technology can constrain loyalty ceilings without producing linear attitudinal gains. Together, these results establish a fourfold necessity sufficiency classification that differentiates baseline requirements, enabling conditions, amplifiers, and indirect drivers of loyalty formation.

This study contributes to SERVQUAL theory by demonstrating that in digitally me-

diated hospitality contexts, peer-generated online content now surpasses direct provider responses in shaping service quality perceptions, suggesting that the traditional provider-to-consumer quality signaling pathway requires reconceptualization. The findings also refine Customer Engagement theory: the NCA result revealing engagement as a sufficient accelerator rather than a necessary precondition challenges the assumed centrality of engagement in loyalty formation models. Regarding AI adoption, the divergence between a non-significant SEM path and a necessary NCA status suggests that technology can operate as an infrastructural necessity without producing linear attitudinal gains, contributing to the augmentation perspective in Technology Acceptance literature. Methodologically, the dual SEM–NCA approach demonstrates how a fourfold necessity–sufficiency classification yields resource allocation logic unavailable from either method alone. Several limitations should be acknowledged. The cross-sectional design precludes inference about how these relationships evolve over time, and the regional focus on western Thailand may constrain generalisability to other markets and hotel categories. AI was measured through perceptions rather than actual interaction behaviour, potentially attenuating its observed linear effect. Future research should adopt longitudinal designs, extend sampling across broader geographic and segment contexts, and incorporate behavioural AI usage metrics to disentangle awareness from interaction effects in shaping customer loyalty.



Recommendations

Theoretical Recommendations

This study raises important issues requiring further investigation. First, Service Quality theory in the digital era must be revised to more comprehensively encompass e-WOM and online information. Traditional SERVQUAL may be insufficient for explaining consumer behavior relying on online platforms. A conceptual framework integrating traditional and digital service quality dimensions should be developed. Second, findings regarding AI open opportunities to study Technology Paradox in Service Encounters. Theory explaining conditions under which technology genuinely adds value and when it creates anxiety should be developed by integrating TAM with Psychological Ownership Theory and Human-Robot Interaction Theory. Third, the use of NCA alongside SEM should be promoted in business research.

Best practices for integrating both methods should be developed, including interpretation of potentially contradictory results.

Research Limitations

This study has several limitations. First, the data were collected only from respondents in the Western Thailand tourism context, which may limit generalizability. Second, the sample is concentrated in the 16–25 age group (48.8%), which may not represent the broader tourist population. Third, self-reported survey data introduces response bias possibilities. Fourth, the cross-sectional design limits causal inference. Fifth, the AI construct was measured through perceived usefulness rather than actual usage. Future research should employ longitudinal designs, broader geographic sampling, actual AI usage metrics, and experimental approaches.

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