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How AI-Driven Service Quality Shapes Purchase Intention Toward Smart Hotels: The Mediating Roles of Perceived Value and Satisfaction

Kun-Da Ho

Department of Agricultural Economics, National Taiwan University, Taipei, Taiwan

E-mail: tony.kptw@gmail.com

Wen-Tsung Wu (Corresponding author)

Chinese Sustainable Innovation and Development Association (CSIDA), Taipei, Taiwan

E-mail: roywu070679@gmail.com

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Abstract

The rapid diffusion of artificial intelligence (AI) in the hospitality industry has given rise to AI-enabled smart hotels that provide contactless check-in, robotic service, intelligent guest rooms, and AI-based customer service. Understanding what drives consumers to adopt such hotels has become an important issue for both scholars and practitioners. Drawing on the service quality–perceived value–satisfaction framework, this study examines how AI-driven service quality shapes consumers' purchase intention toward smart hotels, and whether perceived value and satisfaction mediate this relationship. Based on a questionnaire survey of the general public, 300 valid responses were collected and analyzed using exploratory factor analysis, reliability analysis, correlation analysis, hierarchical multiple regression, and bootstrap mediation analysis. The results show that AI-driven service quality significantly and positively affects perceived value ($\beta = 0.537$) and satisfaction ($\beta = 0.331$); perceived value significantly and positively affects satisfaction ($\beta = 0.339$); and perceived value ($\beta = 0.209$), satisfaction ($\beta = 0.335$), and AI-driven service quality ($\beta = 0.216$) all significantly and positively affect purchase intention. A percentile bootstrap procedure with 5,000 resamples shows that the indirect effect of AI-driven service quality on purchase intention transmitted through perceived value and satisfaction is 0.284 (95% CI [0.211, 0.363]), accounting for approximately 57% of its total effect of 0.500. Perceived value and satisfaction therefore act as key partial mediators. The study contributes to the literature on AI adoption in hospitality

and offers practical implications for smart-hotel operators seeking to enhance consumer acceptance of AI-based services.

Keywords: Artificial intelligence, Smart hotels, Service quality, Perceived value, Satisfaction, Purchase intention

1. Introduction

The hospitality industry is undergoing a profound transformation driven by artificial intelligence (AI). AI-enabled smart hotels increasingly deploy contactless check-in and check-out, service robots, voice-controlled and Internet-of-Things (IoT)-based smart guest rooms, and AI chatbots for customer service, reshaping the way accommodation services are delivered and experienced. These technologies reduce the need for face-to-face interaction, improve operational efficiency, and offer guests more personalized and convenient experiences. As AI applications become a key source of competitive differentiation in the accommodation market, understanding the factors that shape consumers' willingness to stay in AI-enabled smart hotels has become a pressing concern for both researchers and practitioners.

International industry reports underscore the speed of this transformation. The global AI-in-hospitality market is projected to grow from about USD 0.23 billion in 2025 to USD 2.28 billion by 2030, a compound annual growth rate of roughly 58.2% (The Business Research Company, 2026). Industry surveys indicate that a large majority of hotels planned to adopt AI by 2025, and that most travel and hospitality executives increased their AI budgets in 2024 (Skift Research, 2024). High-profile deployments illustrate the shift in practice: HotelPlanner reported that its end-to-end AI voice booking assistants, trained on more than eight million recorded reservation calls and fluent in fifteen languages, were handling about 10,000 customer calls a day within weeks of launch (HotelPlanner, 2024). Figure 1 depicts the projected growth of the global AI-in-hospitality market.

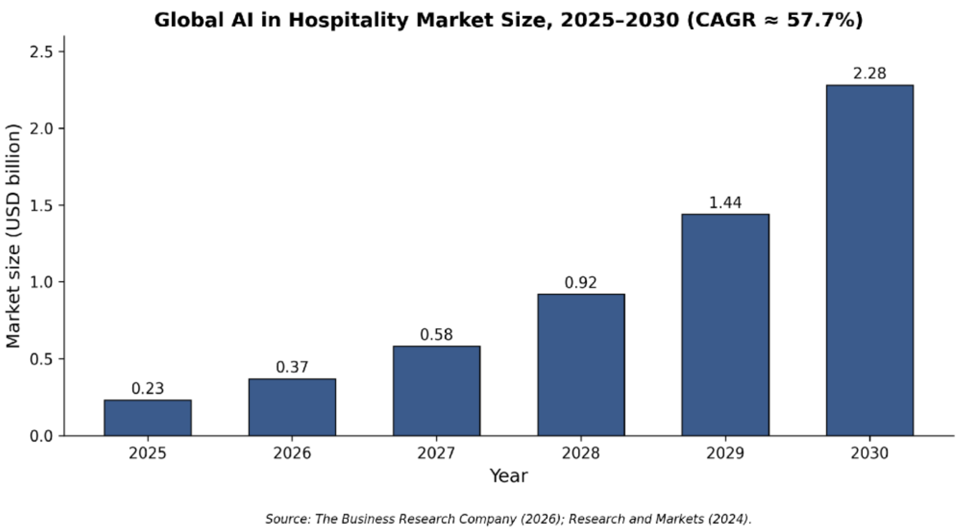

Figure 1. Global AI-in-hospitality market size, 2025-2030

Although prior research has examined smart-hotel technologies and consumer attitudes, relatively little work has explicitly framed smart hotels as AI-driven service environments and tested how AI-driven service quality translates into purchase intention through consumer psychological mechanisms. In particular, the roles of perceived value and satisfaction as mediators in the AI service-quality-to-purchase-intention pathway remain insufficiently examined in the smart-hotel context. This study addresses this gap by drawing on the well-established service quality–perceived value–satisfaction framework and applying it to AI-enabled smart hotels.

What is still unclear is not whether AI matters, but how it converts into a booking decision, and three gaps explain why the question remains open. First, most smart-hotel studies import technology-acceptance constructs such as perceived usefulness and ease of use, and therefore explain the adoption of a device rather than the evaluation of a service; when the service itself is delivered by an algorithm, a robot or a kiosk, what guests act on is a quality judgment, not a usability judgment. Second, perceived value and satisfaction are typically tested one at a time, so the field still lacks evidence on whether the cognitive route and the affective route work in parallel, in sequence, or as substitutes for each other. Third, prior work reports overall effects but rarely decomposes them, which leaves operators without an answer to the question they actually face: which part of the AI-to-intention relationship is worth managing, and how much of it is carried by the guest's own evaluation rather than by the technology itself. This study is therefore necessary because it reframes the smart hotel as a service-quality problem rather than a technology-adoption problem, and because it quantifies, rather than assumes, the psychological route through which investment in AI pays off.

Accordingly, this study has three objectives: (1) to examine the effect of AI-driven service quality on consumers' perceived value and satisfaction with smart hotels; (2) to examine the effects of perceived value and satisfaction on purchase intention; and (3) to clarify the mediating roles of perceived value and satisfaction in the relationship between AI-driven service quality and purchase intention. Based on a survey of 300 respondents, hierarchical multiple regression, and bootstrap mediation analysis, the study provides empirical evidence and managerial implications for smart-hotel operators.

Three contributions follow. Theoretically, the study shows that a framework built for human-delivered services survives the substitution of machine for human agency, and it separates the cognitive and affective mediating routes instead of treating them as interchangeable. Methodologically, it decomposes the total effect into three specific indirect paths, including the serial path through value and then satisfaction, so that the relative weight of each mechanism can be read directly. Practically, it converts these estimates into a managerial rule: AI touchpoints should be judged by the value and satisfaction they generate, not by the number of processes they automate.

2. Literature Review

2.1 AI-Enabled Smart Hotels

Smart hotels integrate artificial intelligence, the Internet of Things, and robotics to deliver accommodation services with minimal human intervention. Typical applications include self-service and contactless check-in, in-room voice assistants and intelligent controls, service and delivery robots, and AI-based customer service. Recent research has examined consumers' receptivity to unmanned and AI-enabled smart hotels, showing that perceived usefulness, security, and technology acceptance shape usage intention (Sthapit et al., 2024). Studies of intelligent services in the hotel industry further indicate that self-service machines, service robots, and intelligent room-control systems significantly influence customer satisfaction (Wu & Cheng, 2025). As AI becomes central to hospitality service delivery, evaluating AI-driven service quality and its consumer outcomes has become an important research theme (Wang et al., 2025).

The broader literature on automation in hospitality has developed quickly but unevenly. Reviews of artificially intelligent device use in service delivery show that research has concentrated on adoption antecedents and on the novelty of the technology, while downstream consumer evaluations remain comparatively thin (Chi et al., 2020; Tussyadiah, 2020). Work on robotic devices in hotels reports that acceptance depends on performance expectancy, effort expectancy and emotion, and that anthropomorphic design cuts both ways (Lin et al., 2020). Meta-analytic evidence on service robots confirms a positive but heterogeneous effect on customer responses, with effect sizes varying by service context and by the degree of human involvement retained (Begum et al., 2025). Two implications matter for the present study: consumer reactions to AI in hotels are not uniform, and the mechanisms that translate AI performance into behavior are still under-specified.

2.2 Service Quality and the SERVQUAL Perspective

Service quality is generally conceptualized as a consumer's overall judgment of the superiority of a service, and the SERVQUAL framework remains the dominant tool for measuring it across service industries. In the context of AI-powered hotel services, researchers have adapted service-quality dimensions to capture robot- and AI-specific attributes such as reliability, assurance, anthropomorphism, and tangibility, and have shown that these dimensions significantly affect consumers' continuance intention (Shi et al., 2025). In this study, AI-driven service quality refers to consumers' overall evaluation of the quality of AI-based services provided by smart hotels.

Two extensions of SERVQUAL are relevant here. The first is E-S-QUAL, which was developed for technology-mediated encounters and replaces interpersonal dimensions such as empathy with efficiency, system availability, fulfillment and privacy (Parasuraman et al., 2005). The second is the recent adaptation of these scales to AI and robot services, where reliability, responsiveness, assurance and data protection remain meaningful but are attributed to a machine rather than to staff (Prentice et al., 2020; Shi et al., 2025). Following this line, the present study treats AI-driven service quality as a service-evaluation construct with a technological referent, rather than as a technology-acceptance construct. This positioning also distinguishes it from perceived usefulness in the technology acceptance model, which captures the instrumentality of a tool rather than the perceived excellence of a service encounter (Davis, 1989; Venkatesh et al., 2012).

2.3 Perceived Value, Satisfaction, and Purchase Intention

Perceived value reflects a consumer's assessment of the benefits received relative to the sacrifices incurred, and customer satisfaction denotes the affective evaluation arising from consumption experience. A substantial body of research establishes that service quality positively influences perceived value and satisfaction, and that these in turn drive behavioral intentions. Importantly, perceived value and satisfaction frequently act as mediators between service quality and behavioral intention (Keshavarz & Jamshidi, 2018). In AI hospitality settings, experience quality and perceived value have been shown to raise overall satisfaction, which subsequently increases repurchase intention toward AI services (Hasan et al., 2023). Building on this evidence, the present study positions perceived value and satisfaction as mediators linking AI-driven service quality to purchase intention.

The quality-value-satisfaction-intention sequence is one of the more robust findings in services research. Cronin et al. (2000) tested it across six service industries and found that quality affects behavioral intentions both directly and through value and satisfaction; Zeithaml et al. (1996) documented the behavioral consequences of service quality across settings; and Sweeney and Soutar (2001) showed that the value construct itself is multidimensional, with functional value dominating in efficiency-oriented services. Applications in tourism and hospitality report the same pattern, with perceived value and satisfaction acting as partial rather than full mediators (Keshavarz & Jamshidi, 2018). What has not been established is whether the sequence survives when the service provider is an algorithm rather than a person, and whether the two mediators retain distinct roles in that setting.

2.4 Theoretical Foundation

The research model rests on three complementary theories. Means-end value theory holds that consumers evaluate an offering by weighing the benefits received against the sacrifices made in money, time and effort (Zeithaml, 1988); it explains why the quality of an AI service should register first as a change in perceived value, since automation mainly alters the sacrifice side of that equation. Expectancy-disconfirmation theory holds that satisfaction is a judgment formed by comparing performance with a prior standard (Oliver, 1980); it explains why AI performance produces an affective response that is separable from the value calculation, and why AI failure is punished so sharply when no staff member is present to repair it. Technology acceptance research supplies the third element: beliefs about a technology, including usefulness, hedonic motivation and habit, exert influence on behavioral intention beyond the evaluation of the encounter itself (Davis, 1989; Venkatesh et al., 2012), which is why a direct path from AI-driven service quality to purchase intention is retained in the model rather than assumed away.

Combining the three yields a specific theoretical claim rather than a generic chain. Cognitive evaluation (value) and affective evaluation (satisfaction) are treated as sequentially ordered rather than parallel alternatives: guests first judge whether an AI service is worth its cost in money, effort and personal data, and that judgment then feeds the overall affective appraisal of the stay. The technology-belief component is expected to survive as a residual direct effect.

The model therefore predicts partial, not full, mediation, and it predicts a serial indirect path in addition to the two simple ones—two predictions that could fail empirically and that distinguish this model from a conventional service-quality chain.

2.5 Research Gap and Positioning of This Study

Three gaps follow from the review. First, a construct gap: smart-hotel research has measured technology beliefs far more often than it has measured AI-driven service quality as an evaluation of an encounter, so the service-marketing tradition and the AI-hospitality literature have developed largely in parallel. Second, a mechanism gap: perceived value and satisfaction are usually modeled as competing mediators, and the serial ordering between them has rarely been tested in an AI setting, so it is not known whether the two routes are complements or substitutes. Third, an evidence gap: studies report total or direct effects without decomposing them, which prevents any statement about how much of the AI effect is actually transmitted by guest evaluations. This study addresses all three by measuring AI-driven service quality as a service-quality construct, by specifying value and satisfaction as both parallel and serial mediators, and by decomposing the total effect with bootstrap estimation of each specific indirect path.

2.6 Research Hypotheses

Based on the service quality–perceived value–satisfaction framework and the above literature, this study proposes the following hypotheses:

Service quality is the main input to the value calculation described by means-end theory (Zeithaml, 1988). In an AI-delivered stay, a check-in completed in seconds rather than minutes, a chatbot that resolves a request at first contact, and a room that responds reliably to voice commands all reduce the guest's non-monetary sacrifice while price is held constant, which raises the benefit-to-sacrifice ratio. Cronin et al. (2000) observed this quality-to-value link across six service industries, and Lin et al. (2020) report the same pattern for robotic hotel services.

H1: AI-driven service quality has a significant positive effect on perceived value.

Expectancy-disconfirmation theory predicts satisfaction when performance meets or exceeds the standard the consumer brought to the encounter (Oliver, 1980). Guests approach AI services with a sharply defined expectation of speed and accuracy; reliable performance confirms it, whereas a failed voice command or an unresolved chatbot loop disconfirms it with unusual force because no staff member is present to recover the service. Evidence from hotels that have deployed self-service machines, service robots and intelligent room controls supports a direct effect on satisfaction (Wu & Cheng, 2025; Prentice et al., 2020).

H2: AI-driven service quality has a significant positive effect on satisfaction.

Value judgments are formed earlier and more quickly than affective ones, and they supply the reference point against which the overall experience is appraised. A guest who concludes that an AI service was worth its cost in money, effort and personal data carries that verdict into the evaluation of the stay as a whole. Both Cronin et al. (2000) and Keshavarz and Jamshidi

(2018) report a significant value-to-satisfaction path once service quality is controlled.

H3: Perceived value has a significant positive effect on satisfaction.

Perceived value also acts directly on behavioral intention, because a favorable benefit-to-sacrifice judgment is itself a reason to repeat the choice regardless of how pleasant the stay felt. This effect is well established in the price-quality-value tradition (Dodds et al., 1991) and has been replicated for AI hospitality services (Hasan et al., 2023).

H4: Perceived value has a significant positive effect on purchase intention.

A direct path from AI-driven service quality to purchase intention is retained for two reasons. Technology beliefs such as usefulness, novelty and habit influence intention over and above the evaluation of a single encounter (Davis, 1989; Venkatesh et al., 2012), and the visible presence of advanced AI can act as a signal of a hotel's overall modernity. Partial rather than full mediation is therefore expected.

H5: AI-driven service quality has a significant positive effect on purchase intention.

Satisfaction is the most consistently documented antecedent of behavioral intention in services research, since a confirmed expectation lowers the perceived risk of choosing the same option again (Oliver, 1980; Zeithaml et al., 1996). In the smart-hotel setting this path is expected to be the strongest of the three direct predictors, because the affective appraisal aggregates the whole stay rather than any single AI touchpoint.

H6: Satisfaction has a significant positive effect on purchase intention.

3. Research Methodology

3.1 Research Framework

This study constructs a research framework comprising four constructs—AI-driven service quality, perceived value, satisfaction, and purchase intention—in which perceived value and satisfaction mediate the relationship between AI-driven service quality and purchase intention. Six hypothesized paths (H1-H6) are specified, as shown in Figure 2.

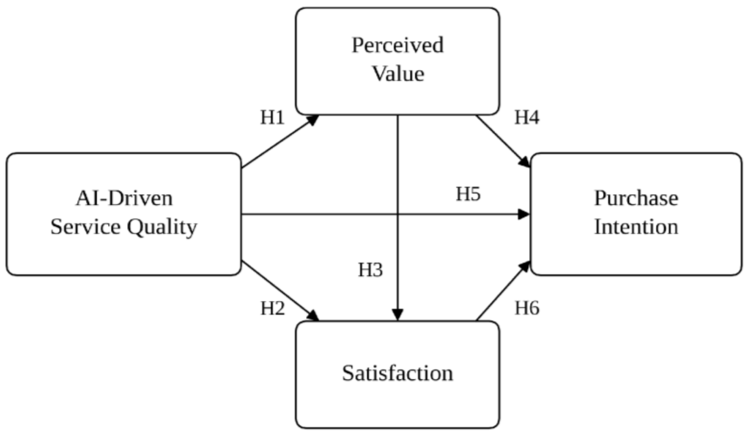

Figure 2. Research framework

3.2 Measurement and Data Collection

The constructs were measured using multi-item five-point Likert scales adapted from established service-quality, perceived-value, satisfaction, and purchase-intention instruments, reworded to fit the AI smart-hotel context: AI-driven service quality (6 items), perceived value (4 items), satisfaction (5 items), and purchase intention (4 items). A questionnaire survey was administered to the general public, and 300 valid responses were obtained. The sample was approximately balanced by gender (146 male, 48.7%; 154 female, 51.3%). Most respondents were aged between 25 and 35 (206, 68.7%), followed by 36-45 (40, 13.3%), under 25 (30, 10.0%), and over 45 (24, 8.0%).

Every item was adapted from a scale with an established psychometric record, and the wording of each item was rewritten so that its referent was an AI-delivered rather than a staff-delivered service. The six AI-driven service quality items were derived from the reliability, responsiveness and assurance dimensions of SERVQUAL (Parasuraman et al., 1988) and from the efficiency, system-availability and privacy dimensions of E-S-QUAL (Parasuraman et al., 2005), with AI-specific wording informed by recent robot- and AI-service quality studies (Prentice et al., 2020; Shi et al., 2025). The four perceived value items follow the quality-for-price logic of Dodds et al. (1991) and the functional-value dimension of Sweeney and Soutar (2001). The five satisfaction items are based on Oliver's (1980) expectancy-disconfirmation measure as operationalized by Cronin et al. (2000). The four purchase intention items are adapted from Zeithaml et al. (1996) and Dodds et al. (1991). All items were scored on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree). The complete instrument, with the source of every item, is reported in Appendix A.

Three procedural steps protected content validity. First, the adapted English items were reviewed by three academics working on service management and two smart-hotel practitioners, who were asked to judge item relevance and clarity; items flagged as ambiguous or double-barrelled were reworded, and one redundant service-quality item was dropped at this stage. Second, because the survey was administered in Traditional Chinese, the instrument was translated and then independently back-translated into English following Brislin's (1970) procedure, with the two versions compared by the research team and discrepancies reconciled before fieldwork. Third, a pilot test was conducted with 30 respondents who matched the screening criteria of the main study. Cronbach's alpha exceeded 0.70 for all four constructs in the pilot (Nunnally, 1978), no respondent reported difficulty with the wording, and the median completion time was about eight minutes; the pilot responses were not included in the main sample.

3.3 Sampling and Survey Procedure

Because the population of smart-hotel guests cannot be enumerated in advance, purposive sampling with an online screening procedure was used rather than probability sampling. A self-administered online questionnaire was distributed in Taiwan through hotel and travel interest groups on social media, university alumni communities, and the researchers' personal networks, with respondents invited to pass the link on to others who met the criteria. The first page stated the purpose of the study, the anonymous and voluntary nature of participation, the intended use of the data and the right to withdraw at any point; respondents proceeded only after giving informed consent. No personally identifying information was collected.

Three screening questions were placed before the measurement items and had to be passed for the questionnaire to continue. Respondents had to be at least 18 years old, to have stayed in a hotel at least once in the previous two years, and to have used or directly observed at least one AI-based hotel service, defined for them as self-service or contactless check-in, an in-room voice assistant or smart-room control system, a service or delivery robot, or an AI chatbot for customer inquiries. Those who failed any screen were thanked and exited. To ensure that all respondents evaluated a common referent, a short description with illustrations of these four AI service types was displayed immediately before the measurement section.

A total of 362 questionnaires were returned between March and May 2025. Of these, 41 were terminated at the screening stage, 12 failed an embedded attention-check item, and 9 were discarded for straight-line responding or for a completion time under two minutes, leaving 300 valid cases for analysis, a usable rate of 82.9%. The achieved sample exceeds the minimum of 10 cases per estimated parameter and is sufficient for detecting a medium effect at conventional power levels in the regression models specified below.

3.4 Analytical Methods

The data were analyzed using exploratory factor analysis, reliability analysis (Cronbach's α), correlation analysis, and hierarchical multiple regression analysis. The Kaiser-Meyer-Olkin (KMO) measure and Bartlett's test of sphericity were used to assess the suitability of the data for factor analysis, and variance inflation factors (VIF) were examined to rule out multicollinearity. The indirect effects of AI-driven service quality on purchase intention were tested with a percentile bootstrap procedure based on 5,000 resamples (Preacher & Hayes, 2008; Hayes, 2018).

4. Results and Discussion

4.1 Validity and Reliability

The KMO values for the four constructs ranged from 0.814 to 0.855, and Bartlett's test of sphericity was significant ($p < 0.001$) for all constructs, confirming the suitability of the data for factor analysis. Each construct extracted a single factor, with all item loadings exceeding 0.70. Cronbach's α values ranged from 0.821 to 0.850, all exceeding the 0.7 threshold, indicating good internal consistency, as shown in Table 1.

Common method bias was also assessed with Harman's single-factor test. When all nineteen items were entered into an unrotated exploratory factor analysis, the first extracted factor accounted for less than half of the total variance, indicating that a single method factor does not dominate the data and that common method bias is unlikely to explain the relationships reported below (Podsakoff et al., 2003).

Table 1. KMO, Bartlett's test, and reliability of the constructs

Construct	**KMO**	**Bartlett's χ^2**	**df**	**p**	**Cronbach's α**
AI-driven service quality	0.855	529.03	15	0.000	0.821
Perceived value	0.815	452.60	6	0.000	0.838
Satisfaction	0.852	509.56	10	0.000	0.833
Purchase intention	0.814	498.30	6	0.000	0.850

4.2 Correlation Analysis

Table 2 presents the means, standard deviations, and correlations among the constructs. All four constructs were rated above the scale midpoint (means 3.88-4.06), and every pairwise correlation was significantly positive, providing preliminary support for the hypothesized relationships. AI-driven service quality was positively correlated with perceived value ($r = 0.537$, $p < 0.001$), satisfaction ($r = 0.513$, $p < 0.001$), and purchase intention ($r = 0.500$, $p < 0.001$), while the strongest association was between satisfaction and purchase intention ($r = 0.553$, $p < 0.001$). The moderate magnitudes indicate that the four constructs are related but empirically distinct.

Table 2. Means, standard deviations, and correlations

Construct	Mean	SD	1	2	3	4
1. AI-driven service quality	4.02	0.54	1			
2. Perceived value	3.92	0.65	0.537***	1		
3. Satisfaction	4.06	0.59	0.513***	0.516***	1	
4. Purchase intention	3.88	0.69	0.500***	0.498***	0.553***	1

Note: N = 300. ***$p < 0.001$.

4.3 Regression Analysis and Hypothesis Testing

Three regression models were estimated to test the hypotheses. In Model 1, AI-driven service quality had a significant positive effect on perceived value ($\beta = 0.537$, $t = 10.98$, $p < 0.001$; $R^2 = 0.288$, $F(1, 298) = 120.64$, $p < 0.001$), supporting H1. In Model 2, both AI-driven service quality ($\beta = 0.331$, $t = 5.94$, $p < 0.001$) and perceived value ($\beta = 0.339$, $t = 6.08$, $p < 0.001$) significantly increased satisfaction ($R^2 = 0.344$, $F(2, 297) = 78.01$, $p < 0.001$), supporting H2 and H3. In Model 3, perceived value ($\beta = 0.209$, $t = 3.69$, $p < 0.001$), AI-driven service quality ($\beta = 0.216$, $t = 3.82$, $p < 0.001$), and satisfaction ($\beta = 0.335$, $t = 6.00$, $p < 0.001$) all significantly increased purchase intention ($R^2 = 0.397$, $F(3, 296) = 65.07$, $p < 0.001$), supporting H4, H5, and H6. All variance inflation factors were below 1.60, indicating that multicollinearity was not a concern. Table 3 summarizes the results.

Table 3. Summary of hypothesis testing

Hypothesis	Path	β	Result
H1	AI-driven service quality → Perceived value	0.537***	Supported
H2	AI-driven service quality → Satisfaction	0.331***	Supported
H3	Perceived value → Satisfaction	0.339***	Supported
H4	Perceived value → Purchase intention	0.209***	Supported
H5	AI-driven service quality → Purchase intention	0.216***	Supported
H6	Satisfaction → Purchase intention	0.335***	Supported

Note: N = 300. Standardized coefficients. ***p < 0.001.

To examine the mediating mechanism more directly, the indirect effects were tested with a percentile bootstrap procedure based on 5,000 resamples. When AI-driven service quality was entered as the sole predictor, its total effect on purchase intention was 0.500 ($t = 9.96$, $p < 0.001$); once perceived value and satisfaction were added, the direct effect fell to 0.216 but remained significant, which indicates partial rather than full mediation. As shown in Table 4, all three specific indirect paths were significant, and the total indirect effect of 0.284 (95% CI [0.211, 0.363]) accounted for 56.8% of the total effect.

Table 4. Bootstrap results for the indirect effects

Path	Standardized effect	95% CI	Result
AI-driven service quality → Perceived value → Purchase intention	0.112	[0.052, 0.177]	Significant
AI-driven service quality → Satisfaction → Purchase intention	0.111	[0.062, 0.166]	Significant
AI-driven service quality → Perceived value → Satisfaction → Purchase intention	0.061	[0.034, 0.092]	Significant
Total indirect effect	0.284	[0.211, 0.363]	Significant
Direct effect	0.216	—	p < 0.001
Total effect	0.500	—	p < 0.001

Note: N = 300; 5,000 percentile bootstrap resamples; standardized coefficients. An indirect effect is significant when the 95% confidence interval excludes zero.

Taken together, the results indicate that AI-driven service quality enhances both perceived value and satisfaction, which in turn drive purchase intention. Because more than half of the total effect of AI-driven service quality on purchase intention is transmitted through perceived value and satisfaction, the two constructs operate as substantive partial mediators rather than as incidental correlates. This pattern is consistent with the service quality–perceived value–satisfaction framework and with prior findings in AI hospitality settings (Hasan et al., 2023; Shi et al., 2025).

4.4 General Discussion

Beyond confirming the six hypotheses, the results reveal several patterns that merit deeper reflection. First, among the three direct predictors of purchase intention, satisfaction was the strongest ($\beta = 0.335$), followed by AI-driven service quality ($\beta = 0.216$) and perceived value ($\beta = 0.209$). This ordering suggests that, in the smart-hotel context, consumers are ultimately persuaded not by the novelty of AI itself but by whether AI delivers a genuinely satisfying experience. Technology is a means rather than an end: an impressive service robot or a slick self-check-in kiosk contributes to purchase intention mainly insofar as it raises perceived value and satisfaction.

Second, AI-driven service quality influenced purchase intention both directly ($\beta = 0.216$) and indirectly through perceived value and satisfaction (total indirect effect = 0.284), with the indirect route carrying roughly 57% of the total effect. Notably, the largest single coefficient in the model is the path from AI-driven service quality to perceived value ($\beta = 0.537$), which suggests that guests read AI-driven service quality first as a value signal. The effect of AI-driven service quality is therefore substantially amplified once it is translated into felt value and satisfaction. From a managerial standpoint, this implies that investment in AI should be judged less by technical sophistication and more by the value and satisfaction it generates for guests—a point that AI adopters in hospitality, in the authors' view, too often overlook when they treat AI deployment as a marketing signal rather than a service-improvement tool.

Third, the serial path running from AI-driven service quality through perceived value to satisfaction and then to purchase intention was also significant (0.061, 95% CI [0.034, 0.092]). This indicates that value perceptions form upstream of satisfaction rather than alongside it: guests appear first to judge whether an AI service is worth what it costs them in money, effort, and personal data, and only then to form an affective evaluation of the stay. At the same time, the bivariate correlations were moderate ($r = 0.50$-0.55) and the model explains about 40% of the variance in purchase intention, which leaves room for meaningful heterogeneity among respondents. Consumers plausibly differ in technology readiness, prior experience with AI services, and privacy concerns, so that the average relationship may mask subgroup differences. This points to an important boundary condition: AI-driven service quality may matter far more for technologically ready and experienced guests than for hesitant or privacy-sensitive ones.

Finally, the findings should be read against the double-edged nature of AI in hospitality. While AI enables contactless convenience, personalization, and efficiency, it also raises concerns about privacy, data security, and the potential loss of the human warmth that has traditionally defined hospitality. The present results—where satisfaction and perceived value, rather than the mere presence of AI, drive purchase intention—can be interpreted as evidence that consumers implicitly weigh these trade-offs. For smart hotels, the strategic challenge is therefore not simply to adopt more AI, but to design AI services that maximize value and satisfaction while safeguarding privacy and preserving a sense of human care.

5. Conclusions and Implications

5.1 Conclusions

This study examined how AI-driven service quality shapes consumers' purchase intention toward smart hotels, and the mediating roles of perceived value and satisfaction. Based on 300 valid responses, hierarchical multiple regression, and bootstrap mediation analysis, all six hypotheses were supported. AI-driven service quality significantly enhances perceived value (β = 0.537) and satisfaction (β = 0.331); perceived value significantly enhances satisfaction (β = 0.339); and perceived value (β = 0.209), satisfaction (β = 0.335), and AI-driven service quality (β = 0.216) all significantly raise purchase intention. The model explains 39.7% of the variance in purchase intention, and perceived value and satisfaction jointly transmit approximately 57% of the total effect of AI-driven service quality, confirming their role as partial mediators. In short, AI-driven service quality is a necessary but not a sufficient condition for consumer acceptance of smart hotels: it converts into purchase intention chiefly by being experienced as valuable and satisfying.

5.2 Theoretical Implications

This study makes three theoretical contributions. First, it extends the service quality–perceived value–satisfaction framework, developed largely for human-delivered services, to an AI-mediated service environment. The finding that the structure of the framework holds when the service provider is an algorithm, a robot, or a self-service interface suggests that the framework is robust to the substitution of machine for human agency, and that AI-driven service quality can be treated as an extension of the SERVQUAL tradition (Parasuraman et al., 1988) rather than as a wholly separate construct.

Second, the study specifies and empirically separates a dual mediating mechanism. Prior AI-hospitality research has often tested perceived value and satisfaction as alternative or interchangeable mediators; the present results show that they operate both in parallel and in series. The two specific indirect paths through perceived value (0.112) and through satisfaction (0.111) are almost equal in magnitude, while the serial path through both (0.061) is smaller but significant. This decomposition clarifies that cognitive evaluation (value) and affective evaluation (satisfaction) are complementary rather than competing explanations of why AI-driven service quality translates into behavioral intention, addressing a gap left by studies that model only a single mediator (Keshavarz & Jamshidi, 2018; Hasan et al., 2023).

Third, the direct effect of AI-driven service quality remained significant after both mediators were entered, indicating partial rather than full mediation. Part of the influence of AI-driven service quality therefore operates through channels that value and satisfaction do not capture—plausibly technology-specific mechanisms such as perceived usefulness, trust in automation, perceived novelty, or privacy risk (Davis, 1989; Sthapit et al., 2024). Theoretically, this argues for hybrid models that combine the service-marketing tradition with technology-acceptance constructs when the service itself is the technology.

5.3 Managerial Implications

For smart-hotel operators, the findings suggest that investing in high-quality AI-based services—reliable contactless systems, responsive AI customer service, and well-designed intelligent guest rooms—strengthens consumers' perceived value and satisfaction and, ultimately, their willingness to stay. Because the strongest single path in the model runs from AI-driven service quality to perceived value (β = 0.537), the most efficient managerial lever is not adding more AI touchpoints but making the existing ones demonstrably worth the guest's money, effort, and personal data.

Second, because perceived value and satisfaction carry roughly 57% of the total effect, AI investment should be evaluated with guest-outcome metrics rather than technology-adoption metrics. Instead of reporting how many processes have been automated, operators would do better to track value- and satisfaction-linked indicators—check-in completion time, first-contact resolution rate for AI customer service, in-room voice-command success rate, and post-stay satisfaction and rebooking rates—and to tie vendor evaluation to these outcomes. A practical rule is that any AI touchpoint that does not measurably improve one of these indicators within a defined pilot period should be redesigned or withdrawn.

Third, the double-edged character of AI implies that value must be communicated and privacy must be visibly protected. Operators should state plainly what guest data an AI service collects, how long it is retained, and how it is used, and should offer a visible human fallback—a staffed desk, a call button, or a chat handover—for guests who prefer human interaction. A human–machine division of labor in which AI absorbs routine, time-sensitive transactions (check-in, room control, standard inquiries) while staff concentrate on discretionary hospitality and service recovery is likely to raise both value and satisfaction, whereas fully unattended automation risks eroding the human warmth on which hospitality brands depend. Staff training and recovery protocols for AI failure should be planned as part of the deployment rather than after it.

5.4 Limitations and Future Research

This study has several limitations, which also indicate directions for future research. First, the data were collected through a cross-sectional questionnaire survey of the general public, and the sample was concentrated in the 25-35 age group (68.7%). This concentration limits generalizability to older travelers and to business travelers, whose evaluation of AI services may differ. Replication with stratified or multi-country samples, and with actual guests of specific smart-hotel properties rather than the general public, would strengthen external validity.

Second, because all variables were measured with self-reported perceptual items collected at a single point in time, common method bias cannot be entirely ruled out and causal direction cannot be established definitively. Future studies should apply procedural remedies such as temporal separation of measurement and statistical remedies such as the marker-variable technique (Podsakoff et al., 2003), and could complement survey data with behavioral indicators such as actual booking or repeat-stay records. Longitudinal or experimental designs would allow the causal ordering of value, satisfaction, and intention to be tested as AI adoption matures.

Third, the model treats AI-driven service quality as a unidimensional construct and explains about 40% of the variance in purchase intention, leaving substantial variance unexplained. Future work could decompose AI-driven service quality into dimensions such as reliability, responsiveness, anthropomorphism, and personalization; incorporate additional constructs such as perceived privacy risk, trust in AI, technology readiness, and perceived novelty; and test moderators such as age, prior AI experience, travel purpose, and privacy sensitivity through multi-group analysis. Estimating the full measurement and structural model simultaneously with structural equation modeling would also address the measurement-error attenuation inherent in regression on summated scales.

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Author contributions

Kun-Da Ho and Wen-Tsung Wu jointly designed the study. Kun-Da Ho was responsible for questionnaire development and data collection. Wen-Tsung Wu performed the statistical analysis and drafted the manuscript, and Kun-Da Ho revised it. Both authors read and approved the final manuscript.

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Competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Informed consent

Obtained.

Ethics approval

Participation was anonymous and voluntary, and informed consent was obtained from every respondent before the questionnaire began; no personally identifying data were collected. The study therefore did not require institutional review board approval.

The journal’s policies adhere to the Core Practices established by the Committee on Publication Ethics (COPE).

Provenance and peer review

Not commissioned; externally double-blind peer reviewed.

Data availability statement

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

Data sharing statement

No additional data are available.

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Declaration on the Use of Generative AI

During the preparation of this manuscript the authors used generative AI tools solely for language editing and readability improvement. The research design, data collection, statistical analysis, interpretation of results and all scholarly arguments are the work of the authors. The authors reviewed and revised all text and take full responsibility for the content of the published article.

Appendix A. Measurement Items and Their Sources

All items were answered on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree). The instrument was administered in Traditional Chinese; the English wording below is the back-translated version (Brislin, 1970).

Code	Measurement item (five-point Likert scale)
	AI-driven service quality (adapted from Parasuraman et al., 1988, 2005; Prentice et al., 2020; Shi et al., 2025)
AISQ1	The AI-based services of this smart hotel (e.g., contactless check-in, AI customer service) operate reliably and without error.
AISQ2	The AI-based services respond to my requests promptly.
AISQ3	The AI-based services are available whenever I need them during my stay.
AISQ4	The AI-based services are easy to operate and the instructions provided are clear.
AISQ5	The AI-based services handle my requests accurately and give me consistent answers.
AISQ6	I am confident that the hotel protects my personal data when I use its AI-based services.
	Perceived value (adapted from Dodds et al., 1991; Sweeney & Soutar, 2001)
PV1	Considering the price I pay, the AI-based services of this smart hotel offer good value.
PV2	The AI-based services save me time and effort during my stay.
PV3	Compared with a conventional hotel at a similar price, this smart hotel offers more benefits.
PV4	Overall, staying at an AI-enabled smart hotel is worthwhile for me.
	Satisfaction (adapted from Oliver, 1980; Cronin et al., 2000)
SAT1	The AI-based services of this smart hotel met my expectations.
SAT2	I am satisfied with my experience of the hotel's AI-based services.
SAT3	The AI-based services made my stay more pleasant.
SAT4	Choosing an AI-enabled smart hotel was a wise decision.
SAT5	Overall, I am satisfied with this smart hotel.
	Purchase intention (adapted from Zeithaml et al., 1996; Dodds et al., 1991)
PI1	I intend to stay at an AI-enabled smart hotel on my next trip.
PI2	I would choose a smart hotel over a conventional hotel offered at a similar price.
PI3	I would recommend AI-enabled smart hotels to my friends and family.
PI4	I am willing to pay a reasonable premium to stay at an AI-enabled smart hotel.

Note: One further service-quality item was deleted after expert review because it overlapped with AISQ2.