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Reshaping Commercial Parking Space: A SEM–ANN Evaluation Based on Integrated IS Success and UTAUT2

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Abstract

The rapid expansion of intelligent technologies within urban commercial built environments has created an urgent need to understand how the quality attributes of infrastructure of smart parking space translate into sustained user behavioral engagement. This study proposes and empirically validates an integrated framework combining the Information Systems (IS) Success Model and the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) to examine continuance usage intention toward intelligent commercial parking space. Cross-sectional survey data from 610 users were analyzed using a hybrid structural equation modeling (SEM) and artificial neural network (ANN) methodology. Results confirm that information quality, service quality, and system quality differentially shape performance expectancy and effort expectancy, which in turn influence user satisfaction and continuance usage intention. Information quality emerged as the most consequential antecedent (normalized relative importance: 100% across both cognitive evaluation models), performance expectancy as the dominant cognitive mediator, and user satisfaction as the most proximal behavioral driver. The non-significant effect of system quality on effort expectancy is interpreted as reflecting a differentiated role of technical reliability in mature smart city environments. Findings provide theoretical contributions to IS success and technology acceptance scholarship in the intelligent built environment domain, and practical guidance for architects, facility managers, and urban planners.

Keywords: intelligent commercial parking space; IS Success Model; UTAUT2; smart building; SEM–ANN



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1. Introduction

The acceleration of urbanization and the parallel expansion of commercial built environments have intensified pressure on cities to manage parking demand and spatial resource allocation with greater efficiency and sustainability [1]. In densely populated urban areas, the inability of commercial parking facilities to meet dynamic occupancy demands represents a critical challenge for urban mobility and the viability of commercial districts [2]. For example, the surge in electric vehicles has created a demand for charging infrastructure in commercial buildings, posing significant challenges to building space and grid layout [3].

Commercial parking facilities, among the most spatially and energetically significant components of urban commercial infrastructure, have historically operated through

manual processes poorly adapted to contemporary demand patterns [4]. The emergence of intelligent parking space, integrating occupancy sensing, automated space guidance, app-based navigation, real-time data delivery, and digital payment processing, represents a significant technological intervention that simultaneously pursues operational efficiency, user experience optimization, and low-carbon facility management, objectives aligned with international building performance standards and urban sustainability policy [5]. In this study, intelligent commercial parking space refers to commercial-use parking environments that integrate networked digital technologies into their physical-spatial fabric. The term is used in the plural and collective sense to denote these facilities as integrated socio-technical environments in which spatial organization, service management, and digital information jointly shape user experience, rather than to denote individual parking stalls [6].

Scholarship on intelligent parking has grown substantially, spanning technical, environmental, and behavioral dimensions. Technical research has examined sensor network architectures, IoT-based infrastructure integration, and real-time occupancy detection as foundations for smart parking deployment [7,8]. Environmental studies have documented intelligent parking's contribution to reducing cruising-related carbon emissions and energy waste [9]. Built environment research has situated intelligent parking within smart building intelligence frameworks and occupant-centered facility management [10]. More recently, studies have begun to examine how intelligent parking intersects with broader smart city trajectories, including autonomous valet parking integration and EV charging infrastructure co-deployment within commercial buildings [11–13].

Despite these advances, significant gaps persist in the smart building behavioral literature. First, studies have overwhelmingly focused on initial adoption intention rather than continuance usage intention, which is a theoretically and practically distinct outcome reflecting sustained post-adoption commitment that more directly determines the long-term operational viability of intelligent parking facilities [14–16]. In the commercial building context, where return on infrastructure investment depends on stable and recurring user engagement, understanding continuance is arguably more consequential than understanding initial uptake. Second, existing behavioral frameworks treat intelligent parking as a generic digital service platform, applying technology acceptance models without adequately grounding their constructs in the physical-spatial and facility management characteristics of the built environment, leaving the relationship between infrastructure quality attributes and sustained user engagement theoretically underspecified and empirically undertested [12,17,18]. In particular, few studies have examined how the design and operational performance of intelligent parking systems shape commercial building spatial layouts, floor area ratio utilization efficiency, or functional zoning, dimensions central to architectural practice and urban planning that remain underexplored in behavioral IS research. Third, prior studies have rarely examined the cognitive and affective mediating mechanisms through which infrastructure quality shapes continuance intention, leaving the behavioral pathway from facility quality to sustained engagement unresolved [4,19].

Addressing these gaps requires a framework that simultaneously captures the quality attributes of intelligent parking infrastructure, the cognitive mechanisms through which users evaluate functional utility and operational ease, and the affective responses that ultimately translate these evaluations into sustained behavioral commitment. To this end, the present study integrates two complementary theoretical frameworks. The IS Success Model provides a validated taxonomy of infrastructure quality dimensions (system quality, information quality, and service quality) that directly characterize the performance attributes of intelligent parking facilities as experienced by building occupants [20,21]. This study draws on UTAUT2 by selecting performance expectancy and effort expectancy as cognitive mediating variables. These two constructs are the most directly relevant to post-adoption,

quality-driven evaluation in this context. Performance expectancy and effort expectancy capture how users translate their quality perceptions into functional and effort-related evaluations. Continuance usage intention is positioned as the behavioral outcome variable [22]. User satisfaction bridges the two frameworks as the affective mediator through which cognitive evaluations are consolidated into behavioral commitment. Together, the two theories construct a complete quality–cognition–affect–behavior chain [23,24].

This study is accordingly guided by the following research questions:

- (1) Which infrastructure quality dimensions most strongly shape users' performance expectancy and effort expectancy in intelligent commercial parking space, and how do their relative effects differ?
- (2) Through what cognitive and affective mediating mechanisms do these quality dimensions transmit their effects on continuance usage intention?
- (3) What is the relative non-linear predictive importance of each construct in determining continuance usage intention?

To address these questions, cross-sectional survey data from 610 users are analyzed using a hybrid SEM–ANN methodology. Unlike studies relying solely on PLS–SEM, this two-stage approach combines theory-driven causal hypothesis testing with data-driven non-linear sensitivity analysis, enabling cross-validation of the structural model and identification of predictive importance rankings under flexible functional assumptions. PLS–SEM with bootstrapping tests the hypothesized mediation pathways, while ANN captures non-linear predictive importance across constructs. This study differs from prior smart building acceptance research and generic digital service evaluations by explicitly anchoring its constructs in the physical-spatial and facility management characteristics of commercial parking infrastructure and by targeting continuance usage intention rather than initial adoption. The study contributes a theoretically integrated evaluation framework for intelligent commercial parking infrastructure and provides practical guidance for architects, facility managers, and urban planners engaged in the design and operation of sustainable commercial building environments.

2. Literature Review and Hypothesis Development

2.1. Theoretical Framework Integration

The proliferation of intelligent technologies within commercial built environments has generated growing scholarly interest in how users evaluate and sustain engagement with smart building systems [11]. Intelligent commercial parking facilities integrate sensor networks, automated occupancy management, and app-based interfaces into the physical fabric of commercial properties. Although prior research has examined their technical performance and intelligence from architectural and building-management perspectives [25], the behavioral mechanisms through which infrastructure quality translates into users' sustained usage commitment remain underexplored. Addressing this gap requires a framework that bridges the built environment's quality attributes with users' cognitive evaluations and behavioral responses.

This study integrates two complementary frameworks: the Information Systems (IS) Success Model [20,21,26] and the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2; [22]). The IS Success Model supplies the quality antecedents and the satisfaction outcome, while UTAUT2 contributes the cognitive mediators and the behavioral-intention construct. DeLone and McLean [26] reaffirmed over a decade of updates that system quality, information quality, and service quality have an indirect impact on satisfaction and usage through cognition, and emphasized that the model is flexible and can be extended according to specific situations. Following this guidance, this framework supplements the

cognitive mediating variables of UTAUT2, thus constructing a theoretically coherent causal chain from infrastructure quality to continuous behavior commitment.

Building on validated applications across technology-intensive service domains, including smart urban infrastructure and intelligent facility management [27,28], all three quality dimensions of the IS Success Model are retained as exogenous antecedents because they directly characterize the performance attributes users encounter in intelligent parking infrastructure. The model's downstream constructs (system use, individual impact, and net benefits) are excluded because behavioral intention is more precisely addressed by UTAUT2 [29].

UTAUT2 (Venkatesh et al., 2012) extends the original UTAUT [30] with consumer-oriented motivational constructs. Performance expectancy and effort expectancy are retained as cognitive mediators because they have demonstrated the most robust predictive effects on behavioral intention in UTAUT2 research [31–33]. Continuance usage intention is retained as the terminal dependent variable, reflecting a deliberate, experience-informed commitment to continued use rather than a one-time adoption decision.

The remaining five UTAUT2 constructs are excluded on the following theoretical grounds. Social influence exerts its strongest normative effects during initial technology adoption. Once users accumulate direct experience, personal quality evaluations replace peer-driven motivation as the primary behavioral determinant. In continuance contexts, social influence therefore becomes theoretically peripheral to post-adoption commitment [16,22,34,35].

Facilitating conditions refer to perceived resource availability and technical support infrastructure. In the major Chinese and South Korean metropolitan contexts examined in this study, intelligent parking applications and their associated digital infrastructure are already widely deployed and operationally mature. These conditions therefore represent a baseline rather than a variable factor, offering limited explanatory power for continuance behavior [32,36].

Hedonic motivation is most consequential in leisure and entertainment contexts. Commercial parking, by contrast, is a task-completion activity in which users seek functional efficiency and spatial convenience rather than intrinsic enjoyment. Hedonic motivation is therefore substantially less relevant in this utilitarian service context [31,32].

Price value reflects consumer cost-benefit trade-offs when choosing among technology options. In this study, however, parking fees are determined by the facility rather than selected by the user. By the time a user selects a facility, pricing has already been incorporated into the initial access decision. Post-adoption value perceptions are more precisely captured by the IS Success Model's service quality construct and by performance expectancy than by price value as a standalone variable [22,26].

Habit reflects behavioral automaticity that develops through extensive prior use and becomes a meaningful antecedent of intention only after users have transitioned from deliberate evaluation to truly automatic use patterns. This study specifically targets the active quality-evaluation stage of continuance, where satisfaction and cognitive appraisals remain deliberate behavioral determinants and have not yet been supplanted by automatic routines [14,34,37]. Although excluded from the present model, these five constructs represent important directions for future research. Social influence and hedonic motivation are particularly worth revisiting as users progress toward habitual use and as cross-market comparisons introduce greater variability in social norms and contextual pricing sensitivity.

Recent research on intelligent parking facilities has further strengthened the relevance of this comprehensive approach. Channamallu et al. [12] studied users' satisfaction with intelligent parking space, where cognitive evaluation played a partial mediating role. However, their model regarded the quality dimension as a single comprehensive predictor

and did not incorporate the formal cognitive mediating factors specified in the UTAUT2 model. This study expands the focus in three aspects. Firstly, it decomposes quality into the three dimensions of information system success to determine which attributes are the most important. Secondly, it models performance and effort expectations as explicit cognitive mediating factors. Third, it incorporates user satisfaction as an explicit affective mediator connecting cognitive evaluations to continuance usage intention, thereby completing the full quality–cognition–affect–behavior causal chain that existing intelligent parking research has left underspecified. The resulting model (Figure 1) can clearly explore the evaluation paths driven by quality dimensions in intelligent commercial parking space.

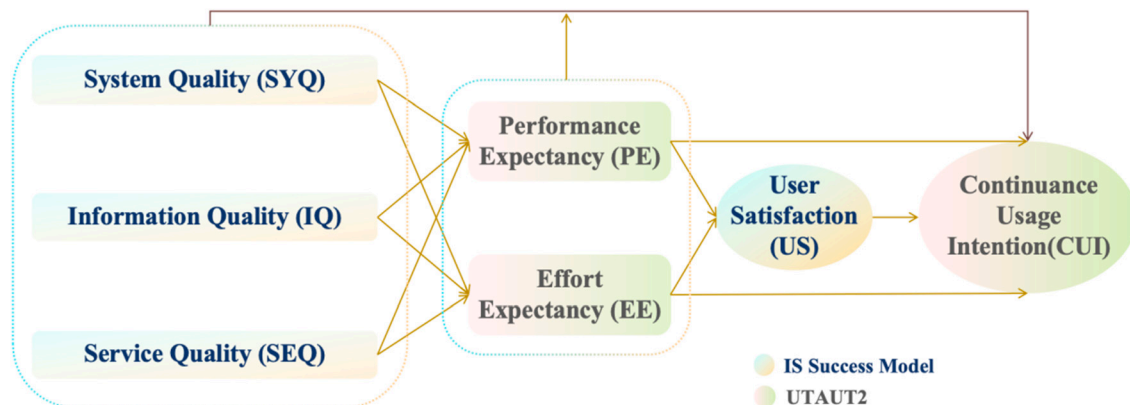


Figure 1. Research model.

2.2. Variable Definitions and Hypothesis Development

2.2.1. System Quality

System quality refers to the technical performance of an information system, including operational reliability, processing speed, functional stability, and the consistency of automated mechanisms [26]. In intelligent commercial parking facilities, it corresponds to what smart-building scholars term technical building intelligence: the precision of occupancy sensor networks, the responsiveness of app-based interfaces, and the accuracy of automated guidance [38,39]. High system quality fosters the belief that the system reliably delivers on its functional promises, enhancing performance expectancy [40,41], while reduced operational friction lowers perceived usage effort and strengthens effort expectancy [42]. Users derive satisfaction from systems performing reliably independently of explicit utility judgments [26,27]. The following hypotheses are proposed:

H1a. *System quality positively influences performance expectancy toward intelligent commercial parking space.*

H1b. *System quality positively influences effort expectancy toward intelligent commercial parking space.*

2.2.2. Information Quality

Information quality refers to the accuracy, relevance, timeliness, completeness, and accessibility of the information delivered by a system [21]. In intelligent commercial parking environments, information quality is expressed through the precision of real-time occupancy data, the reliability of navigation guidance, and the transparency of pricing information, outputs that determine whether users can make efficient spatial decisions within the commercial building facility [43]. Accurate and timely information enhances users' perceptions of how effectively the system supports task completion, elevating performance expectancy [40], while clearly structured outputs reduce the cognitive effort

required to interpret system information and make parking decisions, reinforcing effort expectancy [32,44]. The following hypotheses are proposed:

H2a. *Information quality positively influences performance expectancy toward intelligent commercial parking space.*

H2b. *Information quality positively influences effort expectancy toward intelligent commercial parking space.*

2.2.3. Service Quality

Service quality encompasses the responsiveness, reliability, and problem-resolution efficacy of the support infrastructure associated with an information system [45]. In intelligent commercial parking contexts, service quality reflects the human and organizational layer of building facility management, including app-based customer support, maintenance responsiveness, and real-time issue resolution, that underpins users' trust in the facility's operational competence [38]. When service quality is high, users develop confidence that the system will perform reliably, strengthening performance expectancy [42], while accessible support channels reduce the effort burden of resolving system difficulties, contributing positively to effort expectancy [27]. The following hypotheses are proposed:

H3a. *Service quality positively influences performance expectancy toward intelligent commercial parking space.*

H3b. *Service quality positively influences effort expectancy toward intelligent commercial parking space.*

2.2.4. Performance Expectancy

Performance expectancy is defined as the degree to which a user believes that using a technology will enhance their task performance [22]. It integrates perceived usefulness [46], outcome expectations, and relative advantage, reflecting users' instrumental evaluation of the system's functional value. In intelligent commercial parking space, performance expectancy captures users' beliefs about whether the system improves parking efficiency, reduces search time, and simplifies navigation and payment. This also relates to the sustainability of automotive mobility and land use [13]. As a cognitive mediating variable, performance expectancy translates objective quality perceptions into subjective utility evaluations [40,47], consolidating into user satisfaction as functional expectations are met through accumulated use. It also directly motivates continued engagement, as users who derive tangible benefit from the system have a rational basis for sustained commitment [22,34]. Direct and indirect paths together reflect the complete causal chain [48]. The following hypotheses are proposed:

H4a. *Performance expectancy positively influences user satisfaction with intelligent commercial parking space.*

H4b. *Performance expectancy positively influences continuance usage intention toward intelligent commercial parking space.*

H4c. *Performance expectancy mediates the relationship between system quality and continuance usage intention toward intelligent commercial parking space.*

H4d. *Performance expectancy mediates the relationship between information quality and continuance usage intention toward intelligent commercial parking space.*

H4e. *Performance expectancy mediates the relationship between service quality and continuance usage intention toward intelligent commercial parking space.*

2.2.5. Effort Expectancy

Effort expectancy refers to the perceived ease of use associated with a technology, synthesizing perceived ease of use [46] and complexity [22]. In intelligent commercial parking contexts, effort expectancy reflects users' assessments of interface intuitiveness, the straightforwardness of navigation and payment processes, and the ease of completing routine parking tasks. Effort expectancy shapes user satisfaction by determining the experiential quality of the user–system interaction [20,40]. It also directly influences continuance intention, as operationally burdensome systems promote discontinuance while effort-minimizing systems sustain engagement [34]. The following hypotheses are proposed:

H5a. *Effort expectancy positively influences user satisfaction with intelligent commercial parking space.*

H5b. *Effort expectancy positively influences continuance usage intention toward intelligent commercial parking space.*

H5c. *Effort expectancy mediates the relationship between system quality and continuance usage intention toward intelligent commercial parking space.*

H5d. *Effort expectancy mediates the relationship between information quality and continuance usage intention toward intelligent commercial parking space.*

H5e. *Effort expectancy mediates the relationship between service quality and continuance usage intention toward intelligent commercial parking space.*

2.2.6. User Satisfaction

User satisfaction is defined as users' overall affective evaluation of their cumulative experience with an information system, integrating functional, informational, and service-related impressions into a unified judgment of whether the system has met their needs [21]. In the intelligent commercial parking context, it reflects the holistic evaluative stance that building users develop through repeated engagement with the parking space, encompassing technical reliability, information quality, service responsiveness, and overall ease of use [12]. Within the IS Success Model, satisfaction is the experientially grounded affective state most proximal to sustained behavioral commitment [27], a relationship corroborated across digital service and smart infrastructure research [28,47]. The following hypothesis is proposed:

H6. *User satisfaction positively influences continuance usage intention toward intelligent commercial parking space.*

3. Research Methodology

3.1. Questionnaire Design and Data Collection

The survey instrument was designed to capture respondents' usage experience and evaluative perceptions of intelligent commercial parking space. The questionnaire consisted of three parts. The first part collected demographic information. The second part measured the seven focal constructs. The third part assessed continuance usage intention. All constructs were operationalized using validated measurement scales adapted from the prior literature. The complete set of measurement items is presented in Table 1. All

items were rated on a five-point Likert scale, where 1 indicated “strongly disagree” and 5 indicated “strongly agree.”

Table 1. Modified scale measures.

Measure	Scale Items	Factor Loading	Sources
System Quality (SYQ)	SYQ1 The intelligent parking space operates reliably without unexpected failures or errors.	0.838	DeLone & McLean [21]; Petter et al. [27]
	SYQ2 The intelligent parking space responds quickly to my requests and commands.	0.829	
	SYQ3 The intelligent parking space is easy to access whenever I need to use it.	0.785	
	SYQ4 The automated functions of the parking space (e.g., space detection, guidance) work accurately and consistently.	0.788	
	SYQ5 The overall technical performance of the intelligent parking space meets my expectations.	0.847	
Information Quality (IQ)	IQ1 The parking space provides real-time space availability information that is accurate and up to date.	0.855	DeLone & McLean [21]; Wixom & Todd [40]; Wang & Liao [28]
	IQ2 The navigation and guidance information provided by the parking space is clear and easy to follow.	0.799	
	IQ3 The parking space provides complete information that I need to make parking decisions (e.g., pricing, availability, directions).	0.834	
	IQ4 The information provided by the parking space is presented in a format that is easy to understand.	0.840	
	IQ5 The parking space delivers information that is relevant and useful to my parking needs.	0.856	
Service Quality (SEQ)	SEQ1 The support services associated with the intelligent parking space respond promptly to my requests or problems.	0.870	Parasuraman et al. [45]; DeLone & McLean [21]
	SEQ2 The parking space’s support infrastructure reliably resolves issues when they occur.	0.854	
	SEQ3 The staff or automated support associated with the parking space are knowledgeable and competent.	0.795	
	SEQ4 The service provided through the parking space’s support channels (e.g., app help, on-site assistance) is of high quality.	0.901	
	SEQ5 I feel confident that any problems I encounter with the parking space will be effectively addressed.	0.810	
Performance Expectancy (PE)	PE1 Using the intelligent parking space helps me find a parking space more quickly.	0.894	Venkatesh et al. [22]; Davis [46]; Limayem et al. [34]
	PE2 Using the intelligent parking space improves my overall parking efficiency.	0.908	
	PE3 Using the intelligent parking space reduces the time and effort I spend on parking-related tasks (e.g., navigation, payment).	0.863	
	PE4 I find the intelligent parking space useful in enhancing my parking experience.	0.843	
	PE5 Using the intelligent parking space enables me to accomplish my parking goals more effectively than conventional methods.	0.856	
Effort Expectancy (EE)	EE1 Learning how to use the intelligent parking space is easy for me.	0.841	Venkatesh et al. [22]; Baptista & Oliveira [49]
	EE2 My interaction with the intelligent parking space is clear and understandable.	0.872	
	EE3 I find the intelligent parking space easy to use.	0.816	
	EE4 Completing parking tasks (e.g., finding a space, making payment) through the system requires minimal effort.	0.794	
	EE5 It is easy for me to become proficient at using the intelligent parking space.	0.873	
User Satisfaction (US)	US1 Overall, I am satisfied with the intelligent parking space.	0.854	DeLone & McLean [21]; Lin et al. [47]
	US2 The intelligent parking space meets my expectations in terms of functionality and reliability.	0.918	
	US3 I am satisfied with the quality of information the parking space provides.	0.838	
	US4 I am satisfied with the service support associated with the intelligent parking space.	0.917	
	US5 The intelligent parking space delivers a better experience than I expected.	0.834	
	US6 Using the intelligent parking space is a pleasant experience.	0.860	
	US7 I am satisfied with my overall experience of using the intelligent parking space.	0.853	
Continuance Usage Intention (CUI)	CUI1 I intend to continue using the intelligent commercial parking space in the future.	0.747	Venkatesh et al. [22]; Tamilmani et al. [32]
	CUI2 I plan to keep using the intelligent parking space on a regular basis.	0.774	
	CUI3 I will continue to use the intelligent parking space rather than switching to a conventional parking space.	0.755	
	CUI4 I expect my use of the intelligent parking space to continue in the long term.	0.810	
	CUI5 I would recommend the intelligent parking space to others based on my continued use experience.	0.840	
	CUI6 I am motivated to continue using the intelligent parking space because it meets my parking needs.	0.784	
	CUI7 If the intelligent parking space is available, I will choose to use it consistently.	0.791	

The research was conducted in China and Republic of Korea. Given that data were collected across two linguistically distinct national contexts, all questionnaire items were subjected to a systematic back-translation procedure following the recommendations of Brislin [50]. The original English instrument was first translated into Simplified Chinese and Korean by bilingual translators with expertise in survey research. Independent back-translations into English were then conducted by separate translators who had no access to the original version. Discrepancies identified through comparison of the original and back-translated versions were reviewed and resolved through iterative discussion to ensure conceptual equivalence and linguistic clarity across all three language versions.

To assess the clarity and comprehensibility of the questionnaire items, a pretest was conducted across both national research contexts. Specifically, 30 participants were recruited in China (drawn from smart parking user communities in Beijing and Shanghai) and 30 in

Republic of Korea (drawn from equivalent communities in Seoul and Busan), all with verified experience using intelligent commercial parking space within the preceding three months. Participants completed the questionnaire online via the same distribution channels used in the main survey, and provided written feedback on item wording, ambiguity, and comprehensibility through open-ended comment fields appended to each scale section. Minor revisions were implemented based on this feedback to improve item clarity and contextual appropriateness in both language versions. Data collected during the pretest were excluded from the final analytical dataset.

To ensure data quality and mitigate common method bias, the questionnaire incorporated several validity assurance mechanisms [51]. Attention check items, consisting of instructed-response questions embedded at two points within the survey, were used to identify inattentive respondents. Additionally, response time monitoring was applied to filter submissions completed in an implausibly short duration, and reverse-scored items were included in selected constructs to detect random or acquiescent responding.

3.2. Data Collection and General Demographics

The survey was administered exclusively online over a continuous three-month period. The research team distributed questionnaires via online links through smart parking service user communities, commercial property management platforms, and social media discussion groups in major cities in China and Republic of Korea. All distribution channels were digital. As the primary hubs of smart city development and intelligent commercial infrastructure investment in their respective countries, major cities in China and Republic of Korea provide the highest concentration of intelligent parking space and experienced users, ensuring both sampling adequacy and contextual relevance [19,52]. Respondents were required to be users aged 18 or older who had used smart commercial parking space within the past three months. A total of 800 questionnaire responses were collected. Following data cleaning procedures, including the removal of responses that failed attention checks, exhibited excessive response time deviations, or contained missing values across key items, 610 responses were retained for the final analysis, yielding a retention rate of 76.3%, exceeding the recommended value of at least 10 observations per item [53]. Of the 610 retained responses, 299 were from China and 311 from Republic of Korea. Preliminary comparisons of construct mean scores across the two national subsamples revealed no statistically significant differences, providing initial support for the appropriateness of pooled analysis.

The sample was relatively balanced in terms of gender, with 46.6% male and 53.4% female respondents. Most participants were middle-aged, particularly those aged 40–49 years (28.5%), followed by the 30–39 (23.8%) and 50–59 (23.0%) groups. In terms of education, respondents generally had a relatively high educational level, with the largest proportion holding a bachelor's degree (45.1%), followed by a master's degree (23.0%) and a high school diploma (21.8%). Regarding frequently used commercial parking types, indoor parking garages (43.9%) were the most common, followed by roadside parking space (24.9%), indicating that the sample is relevant to the study of intelligent commercial parking facilities. Most respondents had moderate driving experience, mainly 2 years (29.7%) or 3 years (28.9%), and the majority used commercial parking space 1–2 days per week (44.6%) or rarely (29.2%). Overall, the sample demonstrates reasonable diversity in demographic characteristics, parking experience, and usage frequency, providing an appropriate basis for analyzing users' perceptions and continuance intention toward intelligent commercial parking space.

3.3. Data Analysis Methods

This study adopts a two-stage hybrid analytical framework integrating structural equation modeling based on partial least squares (PLS-SEM) and artificial neural networks (ANN). This combined strategy capitalizes on the complementary strengths of theory-driven and data-driven methods, enabling both the rigorous testing of hypothesized causal relationships and the cross-validation of predictor importance rankings under assumption-free functional specifications.

In the first stage, PLS-SEM was employed via SmartPLS 4.1.1.6 to evaluate the measurement model and test the structural hypotheses. PLS-SEM is a variance-based structural equation modeling technique particularly suited to models with complex mediation structures, non-normal data distributions, and prediction-oriented research objectives [54,55]. The structural model was then assessed using standardized path coefficients estimated through bootstrapping (5000 subsamples). Additional structural model indicators, including effect sizes (f^2), variance inflation factors (VIF) for collinearity assessment, explained variance (R^2), and predictive relevance (Q^2) via blindfolding, were reported to provide a comprehensive account of model fit and predictive adequacy. Mediation hypotheses were tested through bootstrapped indirect effect estimation with 95% bias-corrected confidence intervals following the procedure recommended by Hayes [48]. Before structural model estimation, measurement invariance across the two national subsamples was assessed using the Measurement Invariance of Composites (MICOM) procedure [56], followed by Bootstrap Multi-Group Analysis (MGA) to test the cross-national stability of path coefficients.

In the second stage, ANN analysis was conducted as a robustness check under flexible, assumption-free functional forms and to compute the relative importance of each predictor in determining continuance usage intention [57]. Although ANN is capable of detecting non-linear relationships, its primary function here is to validate whether the predictor importance rankings identified by PLS-SEM remain stable when linearity and distributional assumptions are relaxed. ANN is a machine learning technique modeled on the structure of biological neural networks, consisting of interconnected processing nodes organized into input, hidden, and output layers linked by weighted connections [58]. The normalized importance scores derived from ANN analysis were used to rank the relative predictive contribution of each construct, providing a data-driven validation of the theoretical pathways identified through PLS-SEM [59]. It is acknowledged that comparisons with additional machine learning methods, such as Random Forest or Support Vector Regression, would further strengthen robustness assessment. Such comparisons are recommended as a productive direction for future research.

4. Data Analysis

4.1. Common Method Bias

Several approaches were employed to assess common method bias (CMB). First, Harman's single-factor test was conducted as a preliminary check. The results indicated that the variance explained by a single factor was 38.2%, which is below the commonly used 50% threshold, suggesting that CMB is unlikely to be a serious concern [60]. Second, this study further examined the full collinearity variance inflation factor (VIF) for each latent variable within the structural model [61]. The VIF values for all latent variables ranged from 1.166 to 1.793, all of which are well below the threshold of 3.3.

Finally, confirmatory factor analysis (CFA) was used to compare the fit of the single-factor model with the theoretical multi-factor model. The results showed that the single-factor model exhibited poor fit ($\chi^2/df = 15.772$, RMSEA = 0.156, GFI = 0.390, AGFI = 0.322, SRMR = 0.142, NFI = 0.370, TLI = 0.350, CFI = 0.384), failing to meet common acceptance criteria. In contrast, the theoretical multi-factor model demonstrated significantly superior

fit ($\chi^2/df = 1.444$, RMSEA = 0.027, GFI = 0.926, AGFI = 0.915, SRMR = 0.062, NFI = 0.944, TLI = 0.980, CFI = 0.982), achieving an overall good level of fit. Furthermore, the AIC and BIC of the multi-factor model were substantially lower than those of the single-factor model (AIC = 1181.112 vs. 11,227.938; BIC = 1613.631 vs. 11,572.187). Taken together, these results indicate that common method bias is unlikely to pose a substantial threat to the conclusions of this study.

4.2. PLS-SEM Analysis

4.2.1. Assessment of Measurement Model

The measurement model was evaluated for indicator reliability, internal consistency reliability, and convergent validity following the two-step assessment procedure recommended by Hair et al. [62]. All factor loadings exceeded the minimum threshold of 0.70, ranging from 0.747 (CUI1) to 0.918 (US2), confirming that each indicator reliably reflects its intended latent variable (Table 1). Internal consistency was uniformly strong, with Cronbach's alpha values ranging from 0.897 to 0.919 and composite reliability (CR) values ranging from 0.900 to 0.920 across all seven constructs, both well above the recommended minimum of 0.70 (Table 2). Convergent validity was assessed through the average variance extracted (AVE), with values ranging from 0.618 to 0.745, all exceeding the threshold of 0.50 established by Fornell and Larcker [63], indicating that each construct accounts for the majority of variance in its associated indicators. These results confirm that the measurement model demonstrates satisfactory reliability and convergent validity across all constructs, providing a sound psychometric foundation for subsequent structural model assessment.

Table 2. Cronbach's α , composite reliability, and average variance extracted.

Variables	Cronbach's Alpha (α)	CR	AVE
CUI	0.919	0.920	0.673
EE	0.905	0.906	0.724
IQ	0.913	0.916	0.745
PE	0.908	0.909	0.731
SEQ	0.905	0.911	0.726
SYQ	0.912	0.918	0.741
US	0.897	0.900	0.618

Discriminant validity was assessed using two complementary criteria: the Fornell–Larcker criterion and the heterotrait–monotrait (HTMT) ratio of correlations. As presented in Table 3, the square root of the AVE for each construct, reported on the diagonal, ranged from 0.786 (US) to 0.863 (IQ), and in all cases exceeded the inter-construct correlations reported in the same row and column. This confirms that each construct shares more variance with its own indicators than with any other construct in the model, satisfying the Fornell–Larcker criterion for discriminant validity. The HTMT statistics, reported below the diagonal, ranged from 0.366 (SYQ–CUI) to 0.684 (US–CUI), all falling well below the conservative threshold of 0.85 recommended by Henseler et al. [64]. The results of both the Fornell–Larcker and HTMT assessments confirm satisfactory discriminant validity within the measurement model, supporting the construct's theoretical distinctiveness.

Table 3. Matrix of Pearson correlation coefficients between constructs and HTMT statistics.

	CUI	EE	IQ	PE	SEQ	SYQ	US
CUI	0.821	0.508	0.452	0.540	0.377	0.339	0.624
EE	0.556	0.851	0.515	0.377	0.460	0.336	0.524
IQ	0.492	0.566	0.863	0.562	0.397	0.456	0.474
PE	0.589	0.414	0.617	0.855	0.541	0.480	0.577
SEQ	0.411	0.505	0.435	0.596	0.852	0.383	0.413
SYQ	0.366	0.368	0.499	0.525	0.421	0.861	0.389
US	0.684	0.580	0.520	0.636	0.455	0.428	0.786

Note: Diagonal values represent $\sqrt{AVE}$, values above the diagonal represent inter-structural correlations, and values below the diagonal represent the HTMT statistics.

4.2.2. Assessment of Structural Model

The structural model was evaluated by examining path coefficients, the coefficient of determination (R^2), and predictive relevance (Q^2). The explanatory power of the model was assessed through R^2 values for each endogenous construct (Table 4). PE ($R^2 = 0.465$) and US ($R^2 = 0.442$) demonstrated substantial explanatory power, while EE ($R^2 = 0.345$) and CUI ($R^2 = 0.474$) achieved moderate-to-substantial levels consistent with behavioral PLS-SEM research [55]. All four endogenous constructs returned Q^2 values greater than zero (PE (0.460), EE (0.337), US (0.297), and CUI (0.255)), confirming adequate predictive relevance throughout the model.

Table 4. Model path coefficients, significance, and F^2 .

Path	Original Sample (β)	Standard Deviation	T Statistics	p Values	Support	VIF	f-Square
EE -> CUI	0.224	0.038	5.956	0.000	Yes	1.394	0.069
EE -> US	0.357	0.033	10.706	0.000	Yes	1.166	0.196
IQ -> EE	0.376	0.038	9.830	0.000	Yes	1.362	0.158
IQ -> PE	0.340	0.030	11.412	0.000	Yes	1.362	0.159
PE -> CUI	0.245	0.039	6.198	0.000	Yes	1.517	0.075
PE -> US	0.443	0.031	14.394	0.000	Yes	1.166	0.301
SEQ -> EE	0.290	0.038	7.669	0.000	Yes	1.265	0.102
SEQ -> PE	0.330	0.031	10.705	0.000	Yes	1.265	0.161
SYQ -> EE	0.053	0.039	1.351	0.177	No	1.344	0.003
SYQ -> PE	0.199	0.036	5.583	0.000	Yes	1.344	0.055
US -> CUI	0.366	0.042	8.625	0.000	Yes	1.793	0.142

The hypothesized structural paths are presented in Figure 2 and Table 4. Of the eleven direct paths, ten were supported at $p < 0.001$. Among the quality-to-PE paths, IQ ($\beta = 0.340$, $f^2 = 0.159$) and SEQ ($\beta = 0.330$, $f^2 = 0.161$) produced comparable medium effects, while SYQ exerted a smaller but significant effect ($\beta = 0.199$, $f^2 = 0.055$), supporting H1a, H2a, and H3a. For the quality-to-EE paths, IQ ($\beta = 0.376$, $f^2 = 0.158$) and SEQ ($\beta = 0.290$, $f^2 = 0.102$) were both significant, supporting H2b and H3b. However, the path from SYQ to EE was non-significant ($\beta = 0.053$, $p = 0.177$, $f^2 = 0.003$), leading to the rejection of H1b, suggesting that technical system reliability does not independently reduce perceived usage effort once information and service quality are accounted for. PE emerged as the strongest predictor of US ($\beta = 0.443$, $f^2 = 0.301$), representing the largest effect size in the model, followed by EE ($\beta = 0.357$, $f^2 = 0.196$), supporting H4a and H5a, respectively. Both PE ($\beta = 0.245$, $f^2 = 0.075$) and EE ($\beta = 0.224$, $f^2 = 0.069$) also exerted significant but small direct effects on CUI, supporting H4b and H5b, indicating that their influence on behavioral intention operates predominantly through US rather than directly. US was the most proximal determinant of

CUI ($\beta = 0.366$, $f^2 = 0.142$), supporting H6 and confirming its role as the critical affective driver of sustained engagement with intelligent commercial parking space.

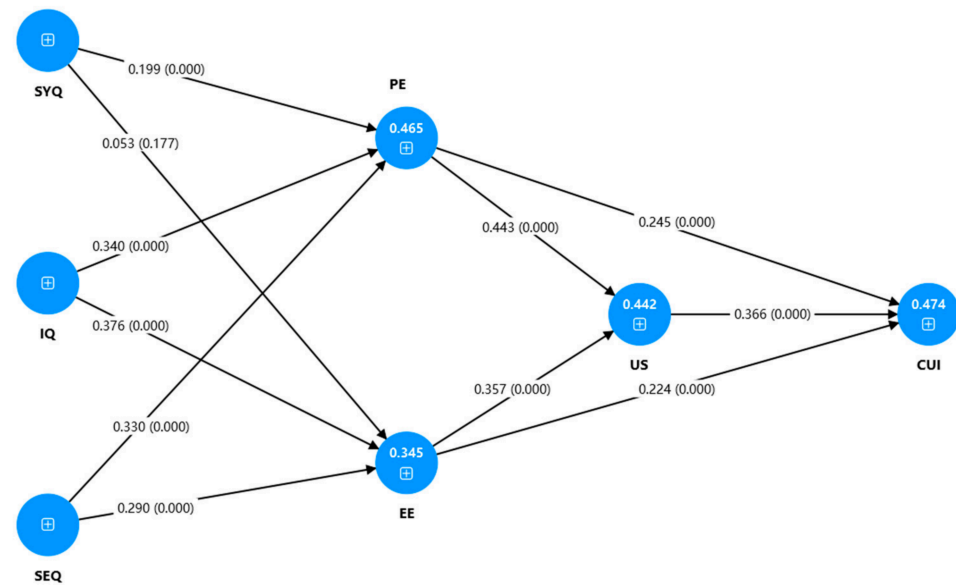


Figure 2. Structural model evaluation results.

4.2.3. Assessment of Mediating Path

Using bias-corrected and accelerated bootstrapping with 5000 subsamples, five of the six specific indirect paths were statistically significant at $p < 0.001$. With respect to performance expectancy as a mediator (H4c–H4e), all three paths were supported: SYQ → PE → CUI ($\beta = 0.049$, $t = 4.292$, $p < 0.001$), IQ → PE → CUI ($\beta = 0.083$, $t = 5.229$, $p < 0.001$), and SEQ → PE → CUI ($\beta = 0.081$, $t = 5.196$, $p < 0.001$), confirming that PE significantly mediates the relationship between each quality dimension and continuance usage intention. Regarding effort expectancy as a mediator (H5c–H5e), IQ → EE → CUI ($\beta = 0.084$, $t = 5.058$, $p < 0.001$) and SEQ → EE → CUI ($\beta = 0.065$, $t = 4.620$, $p < 0.001$) were both supported, confirming H5d and H5e, respectively. However, SYQ → EE → CUI ($\beta = 0.012$, $p = 0.195$) was non-significant, leading to the rejection of H5c, consistent with the earlier rejection of H1b and confirming that system quality does not transmit its effects on CUI through effort expectancy. It should be noted that Table 5 reports two-path specific indirect effects—quality dimension–cognitive mediator–CUI—corresponding to the mediation hypotheses specified in literature review. These paths do not encompass the additional sequential route through user satisfaction.

Table 5. Mediating path coefficients.

Path	Original Sample	Standard Deviation	T Statistics	p Values
IQ → EE → CUI	0.084	0.017	5.058	0.000
IQ → PE → CUI	0.083	0.016	5.229	0.000
SEQ → PE → CUI	0.081	0.016	5.196	0.000
SYQ → PE → CUI	0.049	0.011	4.292	0.000
SEQ → EE → CUI	0.065	0.014	4.620	0.000
SYQ → EE → CUI	0.012	0.009	1.296	0.195

4.2.4. Measurement Invariance and Multi-Group Analysis

Before pooled structural analysis, measurement invariance between the Chinese (Group 1, $n = 299$) and South Korean (Group 2, $n = 311$) subsamples was assessed us-

ing the MICOM procedure [56], followed by Bootstrap MGA to examine the cross-national stability of structural path coefficients.

Firstly, configural invariance was established by confirming that identical measurement indicators, data processing procedures, model specifications, and PLS algorithm settings were applied in both national groups (Step 1).

Secondly, compositional invariance was evaluated via a permutation-based procedure (1000 permutations) (Step 2). As shown in Table 6, all seven constructs achieved original correlations equal to or above the 5.0% permutation quantile, with permutation *p*-values ranging from 0.058 (US) to 0.840 (EE), all exceeding the 0.05 threshold. Although the *p*-value for US (0.058) was proximate to the boundary, its original correlation (0.999) equaled the corresponding permutation quantile, confirming compositional invariance for all constructs.

Table 6. MICOM step 2: Compositional invariance.

Construct	Original Correlation	Correlation Permutation Mean	5.0%	<i>p</i> Value
CUI	1.000	1.000	1.000	0.662
EE	1.000	1.000	1.000	0.840
IQ	1.000	1.000	1.000	0.568
PE	1.000	1.000	1.000	0.343
SEQ	1.000	1.000	0.999	0.429
SYQ	1.000	1.000	0.999	0.230
US	0.999	1.000	0.999	0.058

Third, equality of composite means and variances are reported in Table 7 (Step 3). All constructs showed non-significant differences in both composite means and variances across groups. For composite means, *p*-values ranged from 0.055 (SYQ) to 0.910 (SEQ). For composite variances, *p*-values ranged from 0.171 (SYQ) to 0.988 (EE), all exceeding 0.05. The most proximate result was SYQ's mean difference (original difference = 0.156, *p* = 0.055), which remained within the permutation confidence interval, confirming equality. Taken together, Steps 1–3 establish full measurement invariance across the two national subsamples, confirming the comparability of the measurement model and validating the pooled structural analysis.

Table 7. MICOM step 3: Equality of composite means and variances.

Composite Means	Original Difference	Permutation Mean Difference	2.5%	97.5%	<i>p</i> Value
CUI	0.055	−0.000	−0.162	0.157	0.513
EE	−0.047	0.002	−0.161	0.163	0.564
IQ	0.010	0.002	−0.158	0.164	0.902
PE	0.039	0.001	−0.159	0.160	0.628
SEQ	0.009	0.001	−0.152	0.163	0.910
SYQ	0.156	0.000	−0.158	0.161	0.055
US	−0.019	0.001	−0.157	0.165	0.827
Composite Variances	Original Difference	Permutation Mean Difference	2.5%	97.5%	<i>p</i> Value
CUI	−0.036	−0.001	−0.229	0.235	0.752
EE	0.001	−0.000	−0.211	0.218	0.988
IQ	−0.022	−0.003	−0.266	0.255	0.869
PE	−0.098	−0.000	−0.257	0.253	0.454
SEQ	0.155	−0.000	−0.235	0.240	0.187
SYQ	−0.137	−0.002	−0.193	0.195	0.171
US	−0.027	0.000	−0.199	0.203	0.791

Following MICOM confirmation, Bootstrap MGA was conducted to test whether structural path coefficients differ significantly between Group 1 (China) and Group 2 (Republic of Korea). As shown in Table 8, all eleven direct paths returned two-tailed p -values exceeding 0.05, indicating no statistically significant cross-national differences. The largest inter-group difference was observed for $EE \rightarrow CUI$ ($\Delta\beta = -0.141$, $p = 0.061$), which approached but did not reach significance. Bootstrap MGA on specific indirect effects and total indirect effects is reported in Table 9. All specific indirect paths returned two-tailed p -values exceeding 0.05, confirming that no mediation pathway differed significantly across groups. Total indirect effects likewise showed no significant cross-national differences across all paths. Taken together, the direct path, specific indirect effect, and total indirect effect MGA results collectively confirm that both the structural relationships and the mediation mechanisms in the model are stable across the Chinese and South Korean subsamples, validating the appropriateness of the pooled analysis reported.

Table 8. Bootstrap MGA: Direct effects (Group 1: China; Group 2: Republic of Korea).

	Difference (Group_1–Group_2)	2-Tailed (Group_1 vs. Group_2) p Value
EE -> CUI	−0.141	0.061
EE -> US	0.028	0.669
IQ -> EE	0.023	0.763
IQ -> PE	−0.028	0.631
PE -> CUI	−0.010	0.904
PE -> US	−0.088	0.151
SEQ -> EE	0.073	0.341
SEQ -> PE	−0.016	0.792
SYQ -> EE	0.020	0.805
SYQ -> PE	−0.014	0.841
US -> CUI	0.120	0.143

Table 9. Bootstrap MGA: Indirect effects (Group 1: China; Group 2: Republic of Korea).

Specific Indirect Effects	Difference (Group_1–Group_2)	2-Tailed (Group_1 vs. Group_2) p Value
IQ -> EE -> CUI	−0.048	0.161
SEQ -> PE -> CUI	−0.007	0.809
SYQ -> PE -> CUI	−0.005	0.807
SEQ -> EE -> CUI	−0.025	0.407
SYQ -> EE -> CUI	−0.003	0.838
IQ -> PE -> US	−0.042	0.215
IQ -> EE -> US	0.019	0.619
SEQ -> PE -> US	−0.036	0.287
SYQ -> EE -> US -> CUI	0.006	0.626
SYQ -> PE -> US	−0.024	0.476
SEQ -> EE -> US	0.034	0.311
SYQ -> EE -> US	0.009	0.770
SYQ -> PE -> US -> CUI	0.002	0.913
IQ -> PE -> US -> CUI	0.002	0.896
IQ -> EE -> US -> CUI	0.023	0.198
SEQ -> PE -> US -> CUI	0.004	0.820
SEQ -> EE -> US -> CUI	0.025	0.091

Table 9. Cont.

Specific Indirect Effects	Difference (Group_1–Group_2)	2-Tailed (Group_1 vs. Group_2) <i>p</i> Value
EE -> US -> CUI	0.053	0.154
PE -> US -> CUI	0.021	0.646
IQ -> PE -> CUI	−0.010	0.742
Total indirect effects	Difference (Group_1–Group_2)	2-tailed (Group_1 vs. Group_2) <i>p</i> value
EE -> CUI	0.053	0.154
IQ -> CUI	−0.033	0.448
IQ -> US	−0.023	0.590
PE -> CUI	0.021	0.646
SEQ -> CUI	−0.003	0.947
SEQ -> US	−0.002	0.960
SYQ -> CUI	−0.001	0.970
SYQ -> US	−0.015	0.716

4.3. ANN Analysis

Following the PLS-SEM analysis, this study conducted an Artificial Neural Network (ANN) analysis based on the significant path relationships identified within the SEM. A Feed-Forward Back-Propagation (FFBP) algorithm was employed to predict the outcomes, a process that passes inputs forward and estimates errors backward [65]. Consistent with the procedure outlined by Junjie Yu et al. (2025) [59], the factor scores of the latent variables from the PLS-SEM were used as inputs for the ANN model. To mitigate overfitting, a 10-fold cross-validation technique (90:10 training-to-testing ratio) was implemented, adhering to the guidelines provided by Leong et al. [66].

The ANN analysis in this study comprised four distinct models: Model 1 (Inputs: IQ, SEQ, SYQ; Output: PE), Model 2 (Inputs: IQ, SEQ; Output: EE), Model 3 (Inputs: PE, EE; Output: US), and Model 4 (Inputs: US, PE, EE; Output: CUI). Each of the four ANN models consists of two hidden layers, each containing two neurons, as automatically determined by the SPSS 27 neural network module. This two-layer, two-neuron-per-layer architecture enables the modeling of discontinuous functions while maintaining parsimony. A Sigmoid activation function is applied to neurons in both the hidden layers and the output layer. In the network diagrams presented in Figure 3, positive synaptic weights are represented by grey connections and negative synaptic weights by blue connections, enabling visual identification of each predictor's directional influence.

The prediction accuracy of the ANN model is evaluated using the root mean square error (RMSE) values from the training and test datasets (Table 10) [67]. Across all four ANN models, the mean RMSE values were consistently low for both training and testing phases, ranging from 0.113 to 0.135 (training) and 0.112 to 0.126 (testing), with uniformly small standard deviations indicating high stability across the ten network iterations. The close proximity between training and testing RMSE values across all models confirms that none of the networks exhibit overfitting, and that the models generalize well to unseen data, suggesting that the predictors of continuance usage intention are particularly well-captured by the ANN architecture. These results confirm the robustness and predictive adequacy of all four ANN models.

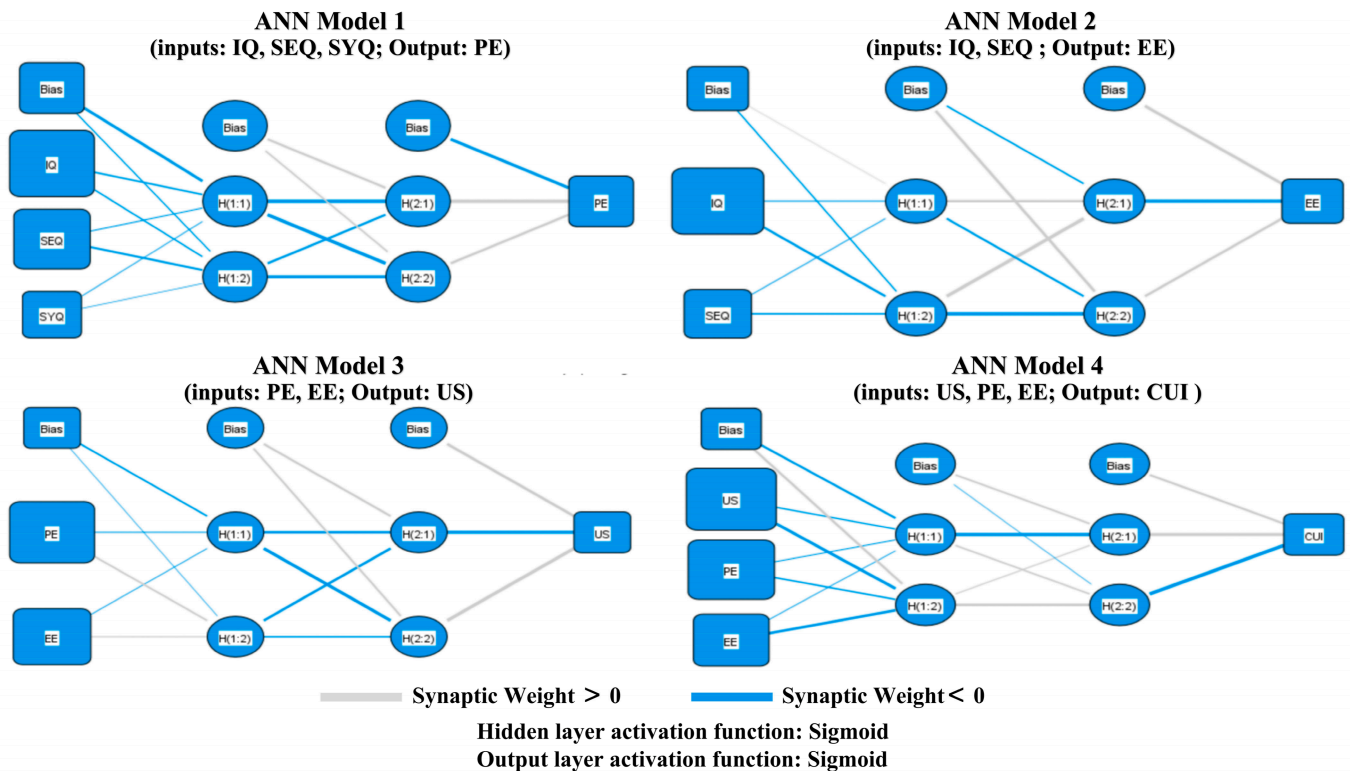


Figure 3. ANN Models 1–4.

Table 10. RMSE values.

Mode	Model 1	Model 2	Model 3	Model 4
Input → Output	IQ, SEQ, SYQ → PE	IQ, SEQ → EE	PE, EE → US	US, PE, EE → CUI
Training RMSE (Mean)	0.113	0.126	0.135	0.116
Training RMSE (SD)	0.001	0.002	0.003	0.001
Testing RMSE (Mean)	0.115	0.126	0.121	0.112
Testing RMSE (SD)	0.011	0.007	0.011	0.008

The normalized relative importance (RI) scores reported in Table 11 are calculated via max-normalization. Each predictor's average importance is expressed as a percentage of the highest-importance predictor in the same model, such that the leading predictor receives 100% and all others are scaled proportionally relative to it. This ranking metric, consistent with standard SPSS neural network output and established SEM-ANN methodology [59], does not require values to sum to 100%, as each score reflects a predictor's importance relative to the within-model maximum rather than a proportional share of a common total.

The ANN sensitivity analysis across all four models identifies clear and consistent patterns of predictor importance. IQ was the dominant predictor of both PE (normalized RI = 100.0%) and EE (100.0%), with SEQ contributing a moderate secondary influence on PE (80.0%) and EE (70.1%), while SYQ exerted the weakest effect on PE (45.9%), indicating that information and service quality are the most consequential upstream drivers of users' cognitive evaluations. In Model 3, PE ranked above EE in predicting US (100.0% vs. 80.6%), confirming that functional utility assessments carry greater weight than perceived ease of use in shaping overall satisfaction. In Model 4, US emerged as the leading predictor of CUI (100.0%), followed by PE (87.9%) and EE (70.4%), with the relatively balanced importance scores across all three predictors suggesting that continuance usage intention is a multidimensional outcome jointly determined by affective satisfaction and cognitive evaluations. These results highlight information quality and user satisfaction as the two most

influential constructs across the full behavioral pathway toward sustained engagement with intelligent commercial parking space.

Table 11. Neural network sensitivity analysis.

Neural Network	Model 1 (Output: PE)			Model 2 (Output: EE)		Model 3 (Output: US)		Model 4 (Output: CUI)		
Inputs	IQ	SEQ	SYQ	IQ	SEQ	PE	EE	US	PE	EE
ANN1	0.464	0.367	0.169	0.625	0.375	0.535	0.465	0.370	0.348	0.281
ANN2	0.487	0.330	0.183	0.571	0.429	0.519	0.481	0.400	0.343	0.257
ANN3	0.466	0.358	0.176	0.548	0.452	0.545	0.455	0.421	0.332	0.247
ANN4	0.427	0.343	0.230	0.538	0.462	0.562	0.438	0.383	0.321	0.295
ANN5	0.401	0.370	0.229	0.544	0.456	0.552	0.448	0.357	0.339	0.304
ANN6	0.420	0.379	0.201	0.546	0.454	0.530	0.470	0.388	0.345	0.267
ANN7	0.452	0.344	0.204	0.687	0.313	0.675	0.325	0.388	0.352	0.260
ANN8	0.455	0.322	0.223	0.638	0.362	0.550	0.450	0.404	0.335	0.262
ANN9	0.434	0.345	0.222	0.629	0.371	0.552	0.448	0.381	0.341	0.279
ANN10	0.435	0.379	0.187	0.592	0.408	0.543	0.457	0.387	0.346	0.267
Average RI	0.444	0.354	0.202	0.592	0.408	0.556	0.444	0.388	0.340	0.272
Normalised RI (%)	100.0	80.0	45.9	100.0	70.1	100.0	80.6	100.0	87.9	70.4
Ranking	1	2	3	1	2	1	2	1	2	3

Note. RI = Relative importance.

The triangulation of PLS-SEM and ANN results demonstrates strong convergent validity across all four models (Table 12). Predictor rankings derived from PLS-SEM path coefficients and ANN normalized relative importance scores are in complete agreement across all ten supported paths, with no ranking inversions observed. This complete agreement indicates that the predictor importance hierarchy identified by PLS-SEM remains stable under the assumption-free ANN specifications within the observed data range. The ANN results confirm that the structural estimates are robust to the relaxation of linearity assumptions. This convergence strengthens confidence in the integrated IS Success Model and UTAUT2 framework as a reliable account of users' behavioral engagement with intelligent commercial parking facilities.

Table 12. Comparison between PLS-SEM and ANN results.

Model	PLS-SEM Path	PLS-SEM Path Coefficient	ANN Normalised RI (%)	Ranking (PLS-SEM)	Ranking (ANN)	Remark
Model 1 (Output: PE)	IQ → PE	0.340	100.0	1	1	Match
	SEQ → PE	0.330	80.0	2	2	Match
	SYQ → PE	0.199	45.9	3	3	Match
Model 2 (Output: EE)	IQ → EE	0.376	100.0	1	1	Match
	SEQ → EE	0.290	70.1	2	2	Match
	SYQ → EE	0.053 (n.s.)	—	—	—	Not supported; excluded from ANN
Model 3 (Output: US)	PE → US	0.443	100.0	1	1	Match
	EE → US	0.357	80.6	2	2	Match
Model 4 (Output: CUI)	US → CUI	0.366	100.0	1	1	Match
	PE → CUI	0.245	87.9	2	2	Match
	EE → CUI	0.224	70.4	3	3	Match

Note. n.s. = non-significant ($p > 0.05$); RI = relative importance; — = not applicable.

Furthermore, the ANN analysis functions as a robustness check that cross-validates the SEM findings rather than as an independent contribution asserting non-linear dynamics. Future studies could provide further evidence on whether non-linear or interaction effects emerge under alternative machine learning specifications.

5. Discussion

The results clarify how the quality attributes of intelligent commercial parking infrastructure shape users' cognitive evaluations, affective responses, and continuance usage intention. Grounded in a hybrid SEM–ANN framework, the findings reveal a coherent pattern in which information quality, service quality, and system quality exert differential influences on performance expectancy (PE) and effort expectancy (EE), which in turn shape user satisfaction and ultimately determine continuance usage intention. Beyond a purely information-systems reading, the findings suggest that intelligent parking should be understood as a socio-technical component of commercial buildings, in which digital information, spatial organization, service management, and user experience jointly determine post-adoption behavior.

5.1. Quality Antecedents and Cognitive Evaluations

Information quality emerged as the strongest predictor of both performance expectancy and effort expectancy. This finding aligns with smart-parking and mobility research, which demonstrates that real-time parking guidance systems reduce search time, travel distance, and inefficient parking behavior [68–70]. Channamallu et al. [12] similarly identified real-time information accuracy as the strongest determinant of smart-parking user evaluations. In the present context, accurate occupancy data, clear route guidance, and transparent pricing help users perceive the system as both useful and easy to use.

Operationally, these findings support layered wayfinding systems integrating app-based pre-arrival guidance, in-building LED zone-availability panels, and decision-point signage at ramp entries, floor transitions, and payment terminals, a configuration already adopted in commercial complexes across Beijing and Shanghai, confirming its viability within existing building constraints. For architects, information quality is therefore a spatial-communication requirement: display placement must account for sightline constraints, illumination levels, and pedestrian flow geometry, with mounting zones and data conduits designated at all decision points. From a spatial planning perspective, guidance systems that reduce cruising time also increase effective space-utilization rates, enabling greater throughput within the same floor area [71].

Service quality was the second-strongest predictor of users' cognitive evaluations, consistent with service-quality research in digital service contexts [72]. In commercial parking, service quality refers not only to online responsiveness but also to the operational capacity of the building-management system. Sensor errors, barrier failures, payment problems, and accessibility-related difficulties require rapid support. Intelligent parking space should therefore be embedded into facility-management routines, fault reporting, maintenance response, customer assistance, and emergency protocols, and integrated with BIM/FM platforms to support asset tracking, operational diagnosis, and lifecycle management [73]. Building operators should translate service quality into measurable management standards, including maximum acceptable response times for app-based support requests, defined intervals for sensor-fault detection and resolution, and availability protocols for on-site assistance during peak hours, creating concrete performance benchmarks that are directly traceable to the user satisfaction outcomes identified in this study.

System quality significantly predicted PE but not EE. This differentiated pattern is best understood through the functional distinction between the two constructs. Technical reliability and processing speed appear to influence users' judgments of task efficiency (PE), by enabling faster and more consistent occupancy detection, guidance, and payment processing, without necessarily reducing the cognitive effort required to interpret information outputs and complete interface interactions (EE). Well-structured and clearly displayed outputs can lower perceived effort independently of the system's underlying technical

speed. This distinction aligns with a hygiene-factor reading of technical reliability. In the mature smart city contexts of China and Republic of Korea studied here, users appear to treat system stability as a baseline expectation that, when met, neither increases nor decreases their sense of operational ease [36]. A further contributing factor may be the sample's educational profile (over 68% of respondents held bachelor's or master's degrees), as higher technological familiarity may reduce the effort variance attributable to system-level performance. These interpretations remain tentative and should be tested through comparative studies across user populations with varying educational profiles and across urban contexts at earlier stages of smart city development.

5.2. Cognitive Mediators and Satisfaction

Performance expectancy was the dominant cognitive mediator, exerting the largest direct effect on user satisfaction and a significant direct effect on continuance usage intention. This supports UTAUT2-based continuance research showing that perceived usefulness remains a central post-adoption mechanism [74]. Users who believe the system meaningfully reduces search time, simplifies entry and exit, supports navigation, and makes payment more predictable develop a correspondingly strong evaluation of the facility experience. The mediation results confirm that PE transmits the effects of all three quality dimensions to continuance intention, indicating that functional-utility assessments constitute the primary cognitive channel through which infrastructure quality is translated into behavioral commitment.

The complete agreement between PLS-SEM path coefficients and ANN normalized importance rankings, with PE consistently ranked first in both Models 3 and 4 across independent analytical paradigms, provides cross-validated, assumption-free confirmation of PE's primacy. This ranking stability has a direct practical implication. Because PE's dominance holds under both linear and flexible functional specifications, improvements in information and service quality yield proportional and predictable gains in functional utility evaluations, without the threshold effects or diminishing returns that would complicate management prioritization decisions.

Effort expectancy played a complementary but secondary role. Its significant effects on satisfaction and continuance intention indicate that ease of use remains important but does not substitute for functional value, consistent with evidence that ease-related beliefs often operate through affective evaluation rather than independently determining continued use [75]. Users who find the system effortless but perceive limited utility are unlikely to develop the satisfaction required for sustained use.

5.3. Satisfaction, Continuance, and Built-Environment Implications

User satisfaction was the most proximal determinant of continuance usage intention, consistent with continuance research emphasizing satisfaction as a central post-adoption mechanism [76] and reaffirming its role as the affective bridge in IS Success theory [26]. ANN analysis confirms this dominance under assumption-free specifications. Satisfaction consolidates repeated experiences of information accuracy, system usefulness, operational smoothness, and service support into a willingness to reuse the facility.

The mediation results further show that information quality generated the largest total indirect effect on continuance intention, supporting the view that information quality influences behavior through both usefulness and ease of use pathways [77]. For building researchers and practitioners, this implies that intelligent parking performance should be evaluated as an integrated information-space-service system rather than a stand-alone digital application. Post-occupancy evaluation should accordingly combine user surveys with operational data, including sensor accuracy, wayfinding performance, congestion patterns, lighting conditions, and facility-management records, linking subjective satis-

faction with measurable building performance through structured feedback loops [78,79]. Facilities should routinely track occupancy display refresh intervals and navigation error rates as proxies for information quality, service-request resolution times and sensor fault rates as indicators of service quality, and system uptime and guidance consistency rates as measures of system quality.

The cross-national measurement invariance confirmed through MICOM and the absence of significant path-coefficient differences in Bootstrap MGA indicate that the mechanism operates comparably across the Chinese and South Korean subsamples. This cross-national stability lends preliminary support to the framework's broader transferability. The underlying behavioral logic—that infrastructure quality shapes cognitive evaluations which consolidate into satisfaction and sustained engagement—is grounded in IS and technology-acceptance frameworks with demonstrated cross-contextual validity [20,26]. Replication in cities at earlier stages of intelligent parking deployment, including markets in Europe, Southeast Asia, and North America, would further test whether the relative importance ordering of quality dimensions and mediators holds as system maturity and user familiarity vary.

Overall, the convergent PLS-SEM and ANN evidence supports the integrated IS Success-UTAUT2 framework and extends its relevance to intelligent commercial parking facilities [59]. Future research should examine whether constructs excluded from the present model, notably social influence and hedonic motivation, become more consequential as users transition from deliberate quality evaluation to habitual use, or as peer sharing of parking experiences generates normative adoption dynamics in commercial building communities.

6. Conclusions

This study proposed and empirically validated an integrated IS Success Model and UTAUT2 framework to examine continuance usage intention toward intelligent commercial parking space, drawing on data from 610 users across major cities in China and Republic of Korea. Using a hybrid SEM-ANN methodology, the study confirmed a complete cognitive-affective behavioral pathway in which system quality, information quality, and service quality shape users' performance expectancy and effort expectancy, which in turn influence user satisfaction and ultimately determine continuance usage intention. Information quality emerged as the most consequential upstream driver (normalized relative importance: 100% across both cognitive evaluation models), performance expectancy as the dominant cognitive mediator, and user satisfaction as the most proximal determinant of sustained behavioral engagement, with all four ANN models demonstrating robust predictive accuracy (training RMSE: 0.113–0.135; testing RMSE: 0.112–0.126). Full measurement invariance was confirmed across the Chinese and South Korean subsamples via MICOM, and Bootstrap MGA revealed no significant cross-national differences in either direct or indirect structural paths, validating the cross-national robustness of the findings.

The study makes three theoretical contributions. First, it constructs a validated integrated framework that bridges the IS Success Model's quality-satisfaction architecture with UTAUT2's cognitive motivational logic, demonstrating that the two theories are empirically complementary in explaining post-adoption behavioral commitment. Second, it extends IS success and technology-acceptance theorizing into the intelligent built-environment domain, establishing a cross-disciplinary foundation that connects information-systems scholarship with smart-building and facility-management research. Third, ANN is applied as a robustness check that cross-validates the structural model's predictor importance hierarchy under assumption-free conditions. The complete absence of ranking inversions across all ten supported paths confirms that the PLS-SEM linear estimates are not materially

distorted by linearity assumptions, providing practitioners with a high-confidence priority ordering for infrastructure investment decisions.

For architects and facility designers, the primacy of information quality underscores the need to consider information infrastructure as a core spatial provision equivalent to lighting and egress, including occupancy displays, directional signage, and pricing panels, which should be embedded at all architectural decision points with dedicated mounting zones and data conduits specified at the design stage. For commercial building operators, the central role of user satisfaction indicates that operational standards for information update latency, service-request resolution time, and system uptime should be established as measurable KPIs, with regular post-occupancy evaluation linking these building performance indicators to user behavioral outcomes. For urban planners and policymakers, the non-significant effect of system quality on effort expectancy in mature smart city contexts suggests that once a baseline level of technical reliability has been achieved, investment returns from further system-level upgrades diminish. Policy incentives should be directed toward information quality standards and service management capacity, particularly in contexts where intelligent parking is newly deployed and users are still forming evaluative judgments. More broadly, the findings support the incorporation of behavioral evaluation frameworks into post-occupancy assessment protocols for intelligent commercial building facilities.

This study is subject to four principal limitations. First, the cross-sectional design precludes examination of how quality evaluations and satisfaction evolve. Future studies should consider diary-study or experience-sampling designs that track users' psychological trajectories from initial adoption through to habit formation. Second, the geographic focus on China and Republic of Korea limits generalizability despite cross-national model stability. Replication in diverse urban contexts, including cities in Europe, Southeast Asia, and North America at varying stages of intelligent parking deployment, is warranted. Third, the exclusion of social influence, hedonic motivation, price value, and habit means that the model does not capture the full range of behavioral determinants. Future research should incorporate these constructs to examine continuance across extended time horizons and more heterogeneous user populations. Finally, reliance on self-reported behavioral intention rather than observed usage behavior is a limitation that future studies employing facility usage records or field-based behavioral tracking could productively address.

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Informed Consent Statement: Before the study began, the researchers provided the participants (non-vulnerable individuals) with an online consent form and participant information sheet via the online survey. They were fully informed that their anonymity would be assured, why the research was being conducted, and how their data would be utilized. They were also informed that there would be no risks to them of participating. Having read and understood the study's purpose, objectives, and how their data would be used, they gave their consent to publish and confirmed that they understood there were no risks to participating. The consent form included contact information for enquiries about the study and withdrawal from participation.

Data Availability Statement: Dataset available on request from the authors.

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