

Smart, Pleasurable, And Influential: Exploring Determinants Of Gen Z's Willingness To Use Airport Service Robots

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ABSTRACT

The rapid integration of service robots in transportation hubs such as airports has transformed how passengers interact with service technologies. As early adopters, Generation Z plays a crucial role in shaping the future of robot-assisted services. This study explores the factors influencing Gen Z passengers' willingness to use airport service robots through the lens of the Cognitive-Affective-Normative framework. Specifically, the study examines the roles of perceived smartness (cognitive), hedonic value (affective), and social influence (normative) in shaping users' willingness to use airport service robots. Using a hybrid approach combining Partial Least Squares Structural Equation Modeling and Necessary Condition Analysis, the findings confirm the significance of all three dimensions. Importantly, perceived smartness of service robots and hedonic value emerge as both sufficient and necessary conditions. The study extends the Cognitive-Affective-Normative framework to the airport context and offers practical implications for enhancing service robot design and engagement strategies tailored to Gen Z users.

KEYWORDS: Airport service robots, Gen Z, Cognitive-Affective-Normative model, Smartness of service robots, Necessary condition analysis

1. Introduction

The proliferation of smart service technologies is transforming the service delivery landscape in public environments, particularly in airports (Booranakittipinyo et al., 2024). The global service robotics market was valued at USD 42.41 billion in 2023 and is projected to grow from USD 47.10 billion in 2024 to around USD 98.65 billion by 2029, representing a compound annual growth rate of 15.9% over the 2024–2029 period (Market and Markets, 2024). In particular, the airport service robot (SR) market was valued at USD 0.9 billion in 2024 and is anticipated to grow to approximately USD 1.91 billion by 2029, reflecting a compound annual growth rate of 16.41% throughout the 2024–2029 forecast period (Research and Markets, 2024). As these technologies become more pervasive, understanding consumer acceptance, especially among digitally savvy users, is essential for ensuring successful implementation and adoption (Kim & Cha, 2024). Among the various demographic cohorts, Generation Z (Gen Z) typically defined as those born between 1994 and 2012, stands out as a highly relevant target due to their early exposure to digital technologies and openness to experimenting with new innovations such as airport service robots (Osakwe et al., 2024).

Despite the growing attention to SRs in the service industry, limited research has explored the psychological mechanisms that shape user willingness to engage with such robots in the airport sector. Prior studies have primarily focused on traditional factors such as usefulness and ease of

use (Osakwe et al., 2024), while under-examining the interplay of emotional and social drivers in shaping behavioral intentions. Additionally, existing literature is often skewed toward general consumer samples and retail settings (e.g. Osakwe et al., 2024; Song & Kim, 2022), leaving a gap in the understanding of technology adoption dynamics among Gen Z travelers in airport contexts.

To examine this phenomenon, the present study draws upon the Cognitive-Affective-Normative (CAN) theoretical framework (Pelegrín-Borondo et al., 2016). This model integrates key dimensions from earlier theories such as TAM, UTAUT, and TRA, offering a more holistic view by capturing not only cognitive appraisals but also affective and normative influences on behavior (Pelegrín-Borondo et al., 2016, 2017). Although developed after these seminal models, the CAN framework has gained traction across diverse domains including healthcare, tourism, and retail (Alesanco-Llorente et al., 2025; Fakfare et al., 2024; Han et al., 2017; Pelegrín-Borondo et al., 2021), yet remains underutilized in airport-based service contexts. By extending the CAN framework to investigate Gen Z's willingness to use airport service robots, this study contributes to its theoretical generalizability and empirical relevance.

Specifically, the research model incorporates three key predictors including perceived smartness of a service robot (cognitive factor), perceived hedonic value (affective factor), and social influence (normative factor), to explain Gen Z's behavioral intention toward using SRs at airports. This focus

marks a departure from traditional constructs such as performance and effort expectancy (Pelegrín-Borondo et al., 2016), by considering emerging constructs like smartness and hedonic values that are increasingly relevant in intelligent service environments. The study further adopts a hybrid analytical strategy, combining Partial Least Squares Structural Equation Modeling (PLS-SEM) with Necessary Condition Analysis (NCA), to uncover both sufficient and necessary conditions that drive user intention—thereby offering more nuanced insights into user–robot interaction.

In doing so, the present study makes three distinct contributions. First, it enriches the theoretical discourse on technology adoption by introducing perceived smartness as a cognitive determinant within the CAN framework. Second, it empirically investigates the affective and normative underpinnings of SR acceptance among Gen Z in the airport setting. Third, by leveraging a hybrid analytical approach, the study provides practical implications for airport operators and technology developers seeking to optimize SR deployment. The remainder of this paper is organized as follows: the next section outlines the theoretical background and hypothesis development, followed by research methods and data analysis. The final sections present the study's findings, discuss theoretical and practical implications, and offer directions for future research.

2. Literature Review

2.1. Cognitive-affective-normative framework

The Cognitive-Affective-Normative (CAN) model initially proposed by Pelegrín-Borondo et al. (2016). This framework is developed by integrating key concepts from foundational frameworks, including the Technology Acceptance Model (TAM) and its later versions (TAM2), the Unified Theory of Acceptance and Use of Technology (UTAUT and UTAUT2), as well as the Theory of Reasoned Action (TRA) and its subsequent extensions (Osakwe et al., 2024; Pelegrín-Borondo et al., 2016). This integrated framework offers a holistic perspective on individuals' behavioral intentions toward emerging offerings by accounting for cognitive evaluations (e.g., performance expectancy, effort expectancy), emotional responses (e.g., positive and negative emotions), and perceived social norms (e.g., social influence or subjective norms) (Pelegrín-Borondo et al., 2016, 2017). Although introduced later than these established models like TAM or UTAUT, the CAN model has recently gained traction in the literature as a robust theoretical lens (Osakwe et al., 2024). Scholars have increasingly applied CAN to diverse contexts such as healthcare technology (Pelegrín-Borondo et al., 2017, 2021; Reinares-Lara et al., 2018), sustainable and smart tourism (Fakfare et al., 2024; García-Milon et al., 2020; Han et al., 2017), service robots and retailing technology (Alesanco-Llorente et al., 2023, 2025; Osakwe et al., 2024; Subero-Navarro et al., 2022), highlighting its predictive value in explaining technology adoption and purchase intentions.

In these contexts, cognitive factors such as performance expectancy (the degree to which using the technology will lead to task efficiency) and effort expectancy (perceived ease of use) consistently emerged as critical

antecedents of intention to adopt (Alesanco-Llorente et al., 2023, 2025; Osakwe et al., 2024). Likewise, affective factors, particularly positive emotions like enjoyment and excitement, were found to exert a strong influence, especially among younger consumer segments such as Gen Z (Osakwe et al., 2024). Subjective norms reflect the perceived social expectations or pressures that influence an individual's decision to engage in or avoid a particular behavior (Pelegrín-Borondo et al., 2016). A substantial body of prior research has investigated their impact on technology adoption, consistently demonstrating that subjective norms play a significant role in shaping individuals' acceptance and use of new technologies (e.g. Alesanco-Llorente et al., 2025; Fakfare et al., 2024; Subero-Navarro et al., 2022).

In the current study, the CAN model is employed to examine Gen Z's willingness to use airport service robots. This contributes to advancing theoretical understanding of service robot adoption in mobility hubs and complements earlier CAN-based research by offering a context-specific lens rooted in the airport environment.

2.2. Smartness of a service robot as cognitive factor

Since the inception of the internet, technological advancements have dramatically transformed the world (Iyer & Bright, 2024). The emergence of artificial intelligence (AI) and the Internet of Things (IoT) has led to a rapid increase in intelligent devices (Hollebeek et al., 2021; McLeay et al., 2021; Pappas et al., 2021). The proliferation of IoT-connected devices is notable (Rokonuzzaman et al., 2022), and consumers are increasingly encountering “smart” objects, as labeled by manufacturers. In current scholarly work, terms like smart object, connected object, intelligent product, and IoT device are often used synonymously to describe these technologies (Imteaj et al., 2022; Langley et al., 2021; Liang et al., 2021; Raff et al., 2020; Sohn & Kwon, 2020; Wang et al., 2024). The concepts of smartness and intelligence in objects are frequently interchanged without a clear consensus on the definition of smartness (Raff et al., 2020). While many studies explore smart objects, few provide a comprehensive measurement or operational definition of the concept. Addressing this gap, building on Rokonuzzaman et al. (2022), this study conceptualizes the Smartness of a Thing (SoT) as a second-order reflective–reflective construct, in which each dimension reflects a distinct yet interrelated aspect of perceived smartness. Specifically, smartness of a service robot reflects through ten reflective first-order dimensions including ability to cooperate, autonomy, environmental agility, learning, novelty, personality, realtime information processing, two-way communication, upgradable, and visual appeal. Collectively, these dimensions capture consumers' holistic perception of smartness based on their direct or indirect experiences with the robot, representing the higher-order latent construct of SoT (Rokonuzzaman et al., 2022).

In the CAN framework, cognitive factors have traditionally been operationalized through constructs such as performance expectancy and effort expectancy (Alesanco-Llorente et al., 2023, 2025). These dimensions assess the perceived usefulness and ease of use of technology and have

been widely validated in numerous adoption studies. Cognitive factors are regarded as essential drivers of behavioral intention, as individuals tend to evaluate a technology's functional benefits and practicality before deciding to engage with it (Alesanco-Llorente et al., 2025; Pelegrín-Borondo et al., 2016). Despite the growing relevance of smart technologies, to the best of the author's knowledge, few studies have explicitly positioned perceived smartness as a cognitive antecedent within the CAN model. Users perceive a robot as truly "smart" not merely based on their ability to complete tasks or perform with usability efficiency, but rather when these technologies contribute meaningfully to improving users' daily lives and demonstrate potential for continual enhancement (Çelebi & Pinar Özemir, 2024). Therefore, it is hypothesized that:

Hypothesis 1: Perceived smartness of an airport service robot positively influences users' willingness to use airport service robots.

2.3. Perceived hedonic value as affective factor

Within the CAN framework, affective factors capture the emotional responses individuals experience when interacting with a given technology (Pelegrín-Borondo et al., 2016). Among these, perceived hedonic value refers to the enjoyment, pleasure, and fun derived from using a product (Wu et al., 2024). Unlike cognitive evaluations based on utility or efficiency, hedonic value represents intrinsic motivation - an emotional appraisal that plays a particularly important role in shaping behavioral intentions, especially among younger consumer groups such as Gen Z (Shah Alam et al., 2024). In the context of SRs, users are likely to gain value from interacting with SRs when they are driven by the enjoyment of fulfilling personal interests or the desire to explore novel and entertaining experiences (Alotaibi et al., 2024; Kim & Cha, 2024).

Numerous studies have demonstrated that perceived hedonic value positively influences individuals' willingness to use service robots, highlighting its role as a key affective factor in technology adoption (Wu et al., 2024; Yuan et al., 2022). Building upon this discourse within the CAN model framework, previous research has shown that positive emotional states, such as joy, enjoyment, happiness, and pleasure, significantly enhance individuals' willingness to engage with service robots (Osakwe et al., 2024). Accordingly, this study proposes that:

Hypothesis 2: Perceived hedonic value exerts a positive influence on users' willingness to use airport service robots.

2.4. Social influence as normative factor

Beyond cognitive and affective influences, normative pressures also play a pivotal role in shaping individuals' technology adoption decisions (Pelegrín-Borondo et al., 2016). Social influence, defined as the degree to which individuals perceive that important others believe they should use a given technology (Zhu et al., 2025), captures this normative dimension (Zhu et al., 2025). Rooted in well-established theories such as the Theory of Reasoned Action and UTAUT, this construct has been widely recognized in explaining behavioral intention across various technological domains

(Osakwe et al., 2024).

In the case of service robots deployed in airport settings, Gen Z users, who are generally more socially connected and trend-sensitive, respond to subtle normative cues, including peer recommendations, influencer endorsements, or broader societal expectations surrounding automation and smart service solutions (Osakwe et al., 2024). This suggests that social influence serves as a relevant factor in predicting willingness to adopt service robots. Moreover, prior empirical studies have consistently demonstrated the positive influence of social influence on users' behavioral intention to adopt emerging technologies, including AI technology and service robots (C. H. Chen & Lee, 2025; Osakwe et al., 2024; Subero-Navarro et al., 2022). Accordingly, the following hypothesis is proposed:

Hypothesis 3: Social influence positively influences Gen Z users' willingness to use airport service robots.

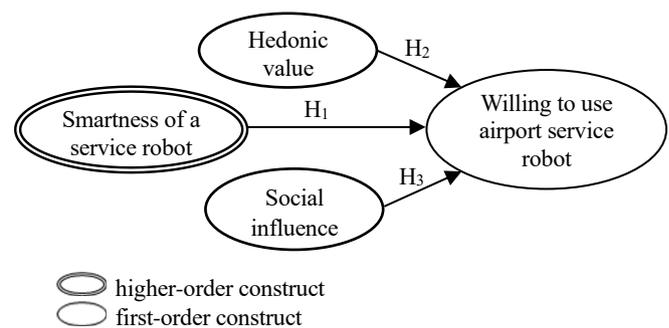


Figure 1: Conceptual model

3. Methods

3.1. Sample and Data collection

Given the study's objective of predicting Gen Z users' willingness to use airport SRs, a quantitative research design was adopted, employing a self-administered survey method. A structured questionnaire in Vietnamese was developed to measure the key constructs derived from the CAN framework. Prior to formal data collection, the questionnaire underwent rigorous refinement through a back-translation process and expert validation. Specifically, two PhD holders in marketing and management, along with three experienced marketing professionals, reviewed and revised the items to ensure conceptual clarity, measurement consistency, and ease of understanding. A pilot study was then conducted with 30 Gen Z participants to test the reliability and comprehensibility of the instrument. The final version of the questionnaire was distributed in printed form and self-administered by respondents. Participants were asked to evaluate their willingness to use smart SRs based on a hypothetical airport scenario involving common customer-service tasks such as check-in, wayfinding, and information requests (Chen & Girish, 2023). All participants were instructed to read a general description of the scenario accompanied by a short video showcasing SRs operating at Incheon International Airport, which served as a realistic visual reference for the study context.

The target respondents were Vietnamese Gen Z individuals who had previous experience interacting with any type of SR in other service contexts (e.g., retail stores, restaurants, hotels, hospitals, or exhibitions). Although SRs have not yet been widely deployed in customer-facing roles at major Vietnamese airports, prior exposure in comparable contexts was considered transferable to the airport setting, as similar cognitive and affective evaluations underlie human-robot interactions across service environments (Belanche et al., 2021a; Ding et al., 2024). This specific group was selected because such prior experience helps minimize the novelty effect and enhances the reliability of evaluations in hypothetical scenarios. Furthermore, existing literature recognizes Gen Z as digital natives and early adopters of emerging technologies (Osakwe et al., 2024), making them an appropriate segment for understanding behavioral intention toward robot-assisted services in airports.

To reflect realistic exposure to airport contexts, the survey was conducted at major airport terminals (Tan Son Nhat and Noi Bai), targeting travelers and airport visitors who fit the eligibility criteria. Participants were recruited using a combination of convenience and purposive sampling techniques. Eligibility criteria required that respondents fall within the Gen Z age range, have had prior interaction with at least one service robot in any context, and voluntarily consent to participate. Data collection took place from March to April 2025.

Out of 500 distributed questionnaires, a total of 452 were collected. After removing incomplete or ineligible responses, a final sample of 377 valid questionnaires was retained for analysis. Participation in the study was entirely voluntary, and no monetary incentives were provided except for a post-card of appreciation upon survey completion. All responses were anonymized and handled with strict confidentiality.

In terms of demographics, 53% of respondents identified as female and 47% as male. Regarding prior robot experience, 33% of participants reported interacting with service robots in retail environments, 27% in restaurants, and 40% in other contexts. These characteristics ensured that the sample represented Gen Z individuals who were not only technologically literate but also had relevant experiential knowledge to assess robotic service applications in airport environments.

3.2. Measurement scales

This study employed a structured measurement model comprising one multi-dimensional construct and three uni-dimensional constructs, all measured using a seven-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree). The multi-dimensional construct, Smartness of an airport service robot, was modeled as a second-order reflective construct consisting of ten sub-dimensions. These dimensions and their items were adapted from Rokonzaman et al. (2022). The three uni-dimensional constructs include hedonic value (four items, Rokonzaman et al., 2022), social influence (three items, Subero-Navarro et al., 2022), and willingness to use airport service robots (four items, Osakwe

et al., 2024). All measurement items were adapted from validated scales in prior literature to ensure conceptual consistency and content validity. (see Appendix)

4. Data analysis and results

4.1. Measurement scales assessment

The research model comprises both uni-dimensional and multi-dimensional constructs. In line with the guidelines proposed by Becker et al. (2012), a two-step approach procedure was applied. Initially, the repeated indicators approach was utilized to calculate the latent variable scores for the first-order constructs, which were then stored for use in the subsequent phase. In the second step, these generated scores were treated as manifest indicators to estimate their associated higher-order constructs. This process followed a reflective-reflective specification, with Stage I used to assess all first-order dimensions (e.g., ten subconstructs of smartness, social influence and willingness to use airport service robots) and Stage II using the latent scores of the smartness dimensions to represent the higher-order construct.

The reliability and validity of the measurement model were rigorously evaluated using established criteria. Following Hair et al. (2017), both Cronbach's alpha and composite reliability were assessed, with all constructs surpassing the recommended threshold of 0.70, as presented in Table 1. Convergent validity was supported by indicator loadings above 0.50 and average variance extracted (AVE) values exceeding 0.50. During the initial analysis in stage I, one item from the Personality (PE) dimension which is "The airport SR has human properties" displayed a low outer loading (0.520), falling below the 0.70 cut-off. In accordance with Hair et al. (2017), this item was removed to enhance construct reliability. After re-estimating, all remaining items showed acceptable outer loadings above 0.70.

To establish discriminant validity, the study applied the Fornell-Larcker criterion and the Heterotrait-Monotrait ratio (HTMT). The results indicated that each item loaded more strongly on its designated construct than on others. Moreover, the square root of each construct's AVE exceeded its correlations with other constructs, and all HTMT values were below the 0.90 threshold (Gold et al., 2001; Henseler et al., 2009) (see Table 2). Collectively, these findings confirmed that the measurement model exhibited satisfactory levels of reliability, convergent validity, and discriminant validity.

Table 1: Reliability and convergent validity assessment

Assessment Stage I						
SoT	Studied constructs	No. of items ^a	α	CR ^b	AVE ^c	Item loading/ highest loading
	AT	3/3	.833	.900	.750	.860/.645, .889/.608, .848/.689
	EA	3/3	.789	.877	.704	.806/.502, .834/.508, .876/.549
	LE	3/3	.710	.838	.634	.759/.516, .800/.436, .828/.469

	NO	3/3	.836	.901	.754	.887/.682, .910/.587, .804/.636
	PE	4/3	.847	.908	.766	.879/.572, .890/.600, .804/.654
	RT	3/3	.838	.902	.755	.853/.592, .856/.497, .897/.596
	TW	3/3	.784	.874	.698	.870/.582, .828/.547, .808/.485
	UP	3/3	.899	.937	.833	.921/.569, .924/.607, .892/.635
	VA	3/3	.887	.930	.817	.904/.634, .943/.668, .863/.573
PH		4/4	.878	.916	.733	.859/.585, .874/.570, .895/.591, .792/.536
SI		3/3	.870	.920	.793	.848/.386, .933/.445, .889/.391
WILL		4/4	.902	.932	.774	.867/.620, .907/.621, .905/.598, .837/.577

Assessment Stage II					
Studied constructs	No of item ^a	α	CR ^b	AVE ^c	Dimension loading/highest loading
SoT	10	.984	.912	.510	.643/.482, .750/.666, .723/.499, .630/.364, .809/.549, .630/.461, .688/.445, .682/.381, .805/.626, .753/.639

Note: ^abased on a 1-7 Likert scale (Initial/Final); ^bComposite Reliability; ^c Average Variance Extracted; α : Cronbach's Alpha; n.a.: not applicable; SoT: Smartness of a service robot; AC: Ability to Cooperate; AT: Autonomy; EA: Environmental Agility; LE: Learning; NO: Novelty; PE: Personality; RT: Realtime Information Processing; TW: Two-way Communication; UP: Upgradable; VA: Visual Appeal; PH: Perceived hedonic value; SI: Social influence; WILL: Willingness to use service robots.

Table 1: Discriminant validity assessment

Assessment Stage I														
Studied constructs	SoT											PH	SI	WILL
	AC	AT	EA	LE	NO	PE	RT	TW	UP	VA				
SoT	AC	.811	.475	.585	.597	.645	.398	.471	.484	.597	.467	.593	.280	.486
	AT	.375	.866	.455	.466	.593	.829	.502	.500	.551	.567	.707	.528	.764
	EA	.450	.372	.839	.796	.728	.336	.545	.577	.661	.625	.593	.176	.528
	LE	.434	.359	.595	.796	.612	.391	.586	.644	.483	.487	.461	.323	.326
	NO	.518	.500	.604	.479	.868	.419	.540	.548	.721	.809	.636	.407	.595
	PE	.317	.696	.276	.304	.352	.875	.443	.492	.377	.419	.533	.487	.526
	RT	.372	.422	.447	.454	.458	.374	.869	.793	.650	.421	.518	.201	.440
	TW	.370	.408	.456	.482	.454	.403	.644	.836	.620	.472	.460	.293	.390
	UP	.490	.481	.560	.386	.637	.330	.565	.519	.912	.685	.652	.234	.709
VA	.381	.489	.525	.387	.693	.363	.366	.397	.612	.904	.708	.469	.581	
PH	.482	.605	.499	.364	.549	.461	.445	.381	.581	.626	.856	.437	.748	
SI	.232	.450	.148	.256	.343	.420	.175	.246	.210	.414	.384	.890	.470	
WILL	.400	.666	.446	.261	.526	.461	.382	.330	.639	.520	.666	.424	.880	

Assessment Stage II				
Studied constructs	SoT	PH	SI	WILL
SoT	0.714	0.788	0.456	0.722
PH	0.718	0.856	0.437	0.748
SI	0.416	0.384	0.890	0.470
WILL	0.684	0.666	0.424	0.880

Note: The lower and upper of the diagonal are bivariate correlations and HTMT ratios, respectively; diagonal bold values are the square root of AVE.

4.2. Assessment of structural model

Following the structural model assessment procedure recommended by Hair et al. (2017), this study first examined collinearity among the predictor variables to ensure the robustness of path coefficient estimates. The variance inflation factor (VIF) values for all independent constructs were found to be below the commonly accepted threshold of 5.0, suggesting that multicollinearity was not a concern. Specifically, the VIF for perceived hedonic value was 2.101, for social influence was 1.232, and for perceived smartness of an airport SR was 2.166. These results confirm the absence of problematic collinearity among the predictors of willingness to use airport SRs.

The SRMR value of 0.080 – less than the threshold (0.10) – verified an acceptable fit of the model for theory

testing (Henseler et al., 2009). In addition, the predictive power and predictive relevance of the proposed research model were assessed through the R² and Q² of the endogenous constructs, respectively. The R² values of 0.26, 0.13 and 0.02 represent substantial, moderate and weak levels of predictive accuracy, respectively (Cohen, 1988), while the predictive relevance of Q² values should be higher than zero. The R² values of willingness to use airport SRs (0.545) all reached the substantial level. The Q² values of the dependent factor were above zero (0.416). These indicate that the exogenous constructs had the substantial explanatory capability and adequate predictive relevance for the endogenous construct in the model. Overall, the quality of the structural model was assured.

To evaluate the direct effects in the structural model, a bootstrapping procedure with 5,000 resamples was performed

to assess the statistical significance of the hypothesized paths (Hair et al., 2017). As shown in Table 3, all hypothesized relationships were found to be statistically significant at the 95% confidence level. Specifically, the effect of perceived smartness of airport SRs on willingness to use airport SRs was the strongest ($\beta = 0.385, t = 5.924, p < 0.001$). Additionally, perceived hedonic value also had a significant and positive impact on willingness ($\beta = 0.338, t = 4.604, p < 0.001$). Lastly, social influence was also positively associated with willingness ($\beta = 0.133, t = 2.595, p = 0.009$). These findings provide empirical support for H_1, H_2, H_3 , and highlight the importance of technological smartness, emotional engagement, and social context in shaping Gen Z consumers' adoption of airport SRs.

Table 3: Hypotheses testing results

Hypotheses	Path	p value	95% CI	Sig.*?
SoT → WILL (H_1)	0.385	0.000	[0.265, 0.521]	Yes
PH → WILL (H_2)	0.338	0.000	[0.184, 0.478]	Yes
SI → WILL (H_3)	0.133	0.009	[0.036, 0.234]	Yes

Note: CI: Confidence intervals; Sig.: Significance; *: $p < 0.05$

4.3. Assessment of necessary conditions using NCA

Necessary Condition Analysis (NCA) was performed using SmartPLS 4.0 to investigate whether perceived smartness of airport service robot, hedonic value, and social influence serve as necessary conditions for willingness to use airport service robots among Gen Z respondents. In line with the recommendations for analyzing continuous variables (Dul, 2016; Dul et al., 2021, 2023), the CR-FDH ceiling line technique was applied to interpret the strength of necessity effects and their corresponding accuracy levels.

Based on the NCA results, perceived hedonic value ($d = 0.209$, accuracy = 99.735%) and perceived smartness of airport service robots ($d = 0.234$, accuracy = 98.939%) were identified as necessary conditions for willingness to use airport service robots, with both showing medium-level necessity effects ($d > 0.1$) according to the guidelines by Dul (2016). In contrast, social influence exhibited a zero-effect size, indicating that it does not qualify as a necessary condition in this context. Notably, both perceived hedonic value and perceived smartness demonstrated high accuracy (above 98%) and effect sizes exceeding their respective 95% confidence intervals (0.069 and 0.066), confirming their robustness. Additionally, the permutation p-values for all three variables were < 0.001 , confirming the statistical significance of the observed necessity relationships (Dul et al., 2021).

Next, the bottleneck analysis results are presented in Table 4, illustrating the minimum level of each necessary condition required to achieve increasing levels of willingness to use airport service robots (WILL). For instance, to reach a 90% level of WILL, at least 3.18 % of perceived hedonic value and 2.65 % of perceived smartness are required, while social influence is not identified as necessary at any level.

Similarly, to achieve the maximum 100% willingness, the minimum required levels rise to 4.78% for perceived hedonic value and 4.51% for perceived smartness, again with social influence remaining non-necessary across all thresholds. In contrast, for lower levels of WILL (e.g., 10% to 40%), the required levels of perceived hedonic value and perceived smartness remain relatively low, and approximately none of the three predictors is necessary at below 10% level of WILL.

Table 4: Bottleneck analysis results

WILL	LV scores - PH	LV scores - SI	LV scores - SoT
0.00%	NN	NN	0.27
10.00%	NN	NN	0.53
20.00%	0.27	NN	0.53
30.00%	0.53	NN	0.53
40.00%	0.80	NN	0.53
50.00%	0.80	NN	0.53
60.00%	0.80	NN	1.33
70.00%	0.80	NN	1.86
80.00%	1.86	NN	2.39
90.00%	3.18	NN	2.65
100.00%	4.78	NN	4.51

Note(s): NN indicates not necessary

5. Discussion

5.1 Theoretical implications

This study makes a significant theoretical contribution by validating the applicability of the CAN model in the context of airport SRs, particularly among Gen Z individuals with prior experience using robotics technologies. While prior research has predominantly examined SR adoption in retail or hospitality settings (e.g. Chang, 2024; Osakwe et al., 2024; J. Wong & Wong, 2025), this study extends the model's scope to a less socially pressured yet highly functional context, airport, where robot interactions often occur individually and task-oriented.

Distinct from previous research that heavily emphasized retail-specific cognitive components such as effort expectancy (e.g. Garcia-Milon et al., 2021; Osakwe et al., 2024), this study underscores the critical role of perceived smartness of an airport SR - a cognitive construct capturing users' evaluations of robot smartness. Our findings reveal that perceived smartness is not only statistically significant but also one of the strongest predictors of Gen Z's willingness to engage with airport SRs. This reaffirms the central role of cognitive evaluations within the CAN framework, particularly in technology-mediated service encounters.

Our results reinforce prior findings that highlight the importance of the affective dimension in shaping user willingness toward service technologies. In our study, hedonic value not only significantly predicts Gen Z's willingness to use airport SRs, but is also identified as a necessary condition through NCA. This underscores the emotional foundations of

engagement with SRs, particularly among young users who value enjoyment, stimulation, and experiential novelty (Osakwe et al., 2024). These findings validate the affective pathway proposed by the CAN model and confirm its relevance in airport environments, where emotional gratification plays a central role in shaping behavioral intentions.

Interestingly, our study indicates a more nuanced role for social influence. While this normative construct positively affects willingness in the PLS-SEM analysis, it lacks substantial effect size and is not classified as a necessary condition. These findings align with emerging perspectives that suggest social influence may operate as a complementary factor in environments with lower social visibility and minimal normative pressure, such as airport terminals (Fraune et al., 2019; Tretter et al., 2025). This contributes to ongoing theoretical discussions by illustrating how contextual characteristics moderate the salience of normative drivers within the CAN framework.

Significantly, by employing a hybrid approach of PLS-SEM and NCA, this study enhances the explanatory depth of the CAN model. The integrated results highlight that while all three constructs, including cognitive, affective, and normative, are statistically relevant, only perceived smartness of a service robot and hedonic value demonstrate both sufficiency and necessity. This dual-method approach not only affirms the robustness of CAN in emerging service settings but also answers recent calls in the technology adoption literature (Magno & Cassia, 2024; Richter et al., 2020) for deeper analytical techniques that distinguish between critical and supportive factors.

In summary, this research offers novel theoretical insights into Gen Z's acceptance of SRs in airports. By advancing the CAN framework through empirical evidence and methodological rigor, it contributes to a more refined understanding of the psychological mechanisms underpinning user interaction with service robots in modern service ecosystems.

5.2. Practical implications

The insights derived from this study hold substantial practical value for airport operators, service managers, and robot developers aiming to enhance Gen Z passengers' engagement with airport service robots. The findings clearly indicate that perceived smartness of a SR, hedonic value, and social influence are factors driving Gen Z's willingness to interact with SRs. By integrating the results from both PLS-SEM-NCA, this study highlights not only which factors are sufficient to influence intention, but also which are necessary prerequisites for this behavioral outcome.

From a managerial standpoint, airport service providers should prioritize the development of SRs that capture the most relevant aspects of smartness for Gen Z users. While the full spectrum of the ten SoT dimensions remains important, prior studies suggest that autonomy, novelty, personality, two-way communication, and visual appeal are particularly influential for Gen Z young consumers (Chen et al., 2022; Magtibay et al., 2025; Wong & Wong, 2025b). Specifically, robots should be

designed to support autonomous service delivery, enabling Gen Z passengers to complete tasks quickly and independently without staff intervention (Schepers et al., 2022). Novel and innovative features, such as unique functions or creative design elements, can help capture Gen Z's interest and differentiate the robot experience (Osakwe et al., 2024; Wu et al., 2024). Adding expressive, human-like personality traits (e.g., friendly greetings, emotional tone) may improve approachability and emotional connection (Magtibay et al., 2025). Moreover, enabling two-way communication through natural dialogue and responsiveness will make interactions more fluid and intuitive (de Oliveira et al., 2024; Gao et al., 2023). Finally, attention to visual appeal, e.g. sleek design, vibrant interfaces, and modern aesthetics, can boost initial engagement and signal technological sophistication (Belanche et al., 2021b; Xin & Liu, 2025). Prioritizing these dimensions will help airports create robot experiences that resonate with Gen Z travelers and encourage greater adoption.

Furthermore, the findings underscore the importance of hedonic value. Gen Z travelers are more likely to engage with service robots when interactions are enjoyable, emotionally satisfying, and memorable (Hu, 2021). Thus, service providers should look beyond functionality and incorporate playful, expressive elements into robot design. Features such as simple gamified interactions or friendly, human-like behaviors can enrich the user affective experience (Pollmann et al., 2023; Riar et al., 2025), especially in low-pressure environments like waiting areas. However, such enhancements must be implemented with care to avoid interfering with safety procedures or operational flow in the airports. Likewise, while social influence showed a smaller effect than cognitive or emotional drivers, it remains meaningful. Service providers can leverage peer-based strategies (Hughes et al., 2019), such as influencer content, short-form user testimonials, or visual cues that others are using the robots, to build social acceptance and reduce hesitation. These approaches should be subtle, well-coordinated, and compliant with airport regulations to ensure they contribute positively without causing disruption. By balancing experiential appeal with safety and efficiency, airports can create engaging yet practical robot interactions for Gen Z passengers.

Lastly, these practical recommendations should serve as a call to action for closer collaboration between airport authorities and robotics developers. To ensure service robots truly align with Gen Z preferences, stakeholders should integrate affective, cognitive, and normative factors into both design and deployment. This can be achieved through concrete initiatives such as pilot projects that test robot prototypes in selected terminals, or co-design workshops where developers work directly with Gen Z users and airport staff to refine features and interaction styles. Such collaborative approaches not only enhance technological fit but also promote operational feasibility and traveler satisfaction, paving the way for more engaging and personalized airport experiences.

5.3. Limitations and future research directions

Despite offering novel contributions to the literature on human-robot interaction in airport contexts, this study is not

without limitations. First, the sample consisted exclusively of Gen Z participants who had prior experience with SRs, which may restrict the generalizability of the findings to other generational cohorts or first-time users. Future studies could adopt a broader sampling frame that includes older passengers or individuals unfamiliar with such technologies to examine generational differences in perceived smartness and technology acceptance.

Second, the study was conducted within the Vietnamese airport context. While this context allows unique insights into SR adoption, it may not fully capture dynamics present in other high-pressure or collectivist settings, such as shopping malls or healthcare facilities. Cross-contextual and cross-cultural validations are therefore necessary to assess the robustness of the CAN model in explaining SR usage across different environments (Chen & Girish, 2023; Osakwe et al., 2024).

Third, although the study identifies perceived smartness, hedonic value, and social influence as key predictors of willingness to use airport SRs, it does not examine the potential mediating or moderating effects of factors such as trend affinity, prior satisfaction, or personal innovativeness. Future research could enrich the current model by integrating these variables to reveal deeper psychological mechanisms underlying behavioral intention.

Fourth, the present study focuses predominantly on quantitative insights derived from PLS-SEM and NCA. While this dual-method approach enhances explanatory power, it may overlook nuanced user perceptions and emotional narratives. Qualitative methods such as in-depth interviews or observational studies could be used to complement and contextualize quantitative findings (Carù et al., 2014), especially regarding how Gen Z users interpret smartness or derive enjoyment from robot interaction.

Lastly, while the construct of perceived smartness was operationalized as a multidimensional concept encompassing ten facets, future research could further refine this scale or examine which dimensions (e.g., learning, visual appeal, personality) matter most in specific service settings. Doing so would not only help optimize robot design but also provide granular guidance for practitioners aiming to enhance user experience through targeted smart features.

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Appendix

Smartness of an airport service robot

(Rokonuzzaman et al., 2022)

Ability to Cooperate

The airport SR fits with other objects.

The airport SR works with other objects.

The airport SR is congruent with other objects.

Autonomy

The airport SR does not need a lot of human inputs to function.

The airport SR works independently.

The airport SR finds its own way.

Environmental Agility

The airport SR scans its environment.

The airport SR reacts to changes in the environment.

The airport SR directly adapts its behavior to the environment.

Learning

The airport SR learns from experience.

The airport SR has an ability to learn.

The airport SR improves itself.

Novel

The airport SR is cutting-edge.

The airport SR is innovative.

The airport SR is original.

Personality

The airport SR has human properties. (Removed)

The airport SR is like a person.

The airport SR behaves like a human being.

The airport SR has human-like personality.

Real-Time Information Processing

The airport SR can process information in real time.

The airport SR retrieves information in real time.

The airport SR offers real-time information.

Two-way Communication

The airport SR enables two-way communication between itself and the user.

The airport SR enables concurrent communication with the user.

The airport SR is interactive with the user.

Upgradable

The airport SR can be improved with current technology.

The airport SR can be upgraded with new technology.

The airport SR is capable of being upgraded with new

technology.

Visual Appeal

The airport SR is visually appealing.

The airport SR is good looking.

The airport SR has a stylish design.

Perceived hedonic value

(Rokonuzzaman et al., 2022)

Using the airport SR is fun.

Using the airport SR is pleasant.

Using the airport SR provides enjoyment.

Using the airport SR is not boring.

Social influence

(Subero-Navarro et al., 2022)

People who are important to me will think that I should use SRs at the airport.

People who influence me will think that I should use SRs at the airport.

People whose opinions I value will prefer that I use the SRs.

Willingness to use airport service robots

(Osakwe et al., 2024)

I predict I will use SRs for making requests at the store.

If available, there is a strong chance that I will ask for assistance from a SR during my visit to the airport.

I could see myself using a SR to make requests at the airport.

Using a SR to make request at the airport is something I would do.