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The Impact of Emotional Factors on Service Robot Acceptance in Global Hospitality: A Mixed-Method Analysis

Küresel Konaklama Sektöründe Hizmet Robotlarının Kabulüne Duygusal Faktörlerin Etkisi: Karma Yöntemli Bir Analiz

Ali Eren BALIKEL[1]

ABSTRACT

The purpose of this study is to investigate how consumers perceive and accept service robots specifically designed for use in thermal hotel environments. To achieve this objective, the research focuses on the roles of positive emotions, negative emotions, and consumers' behavioral intentions toward adopting service robots. Employing a mixed-methods design, the study integrates both qualitative insights and quantitative rigor to examine the interrelationships among emotional and cognitive factors. Data were collected from 458 guests staying at thermal hotels across Türkiye. The analysis was conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM) alongside fuzzy-set Qualitative Comparative Analysis (fsQCA), enabling a robust and multidimensional evaluation of the proposed hypotheses. The findings from PLS-SEM indicate that novelty and satisfaction exert a statistically significant positive influence on consumers' acceptance of service robots, whereas the effects of enjoyment and negative emotions were non-significant. However, fsQCA results revealed that specific combinations of emotional states rather than individual factors alone, can effectively lead to higher acceptance levels of acceptance. These findings provide valuable implications for ***developing*** *strategies for implementing service robot in hospitality environments.*

Keywords: Human-robot interaction, Hotel industry, Technology adoption, PLS-SEM, fsQCA

ÖZ

Bu çalışmanın amacı, tüketicilerin termal otel ortamlarında kullanılmak üzere özel olarak tasarlanmış servis robotlarını nasıl algıladıklarını ve kabul ettiklerini araştırmaktır. Bu amaca ulaşmak için araştırma, olumlu duygu, olumsuz duygu ve tüketicilerin servis robotlarını benimsemeye yönelik davranışsal niyetlerinin rollerine odaklanmaktadır. Karma yöntemli bir tasarım kullanan çalışma, duygusal ve bilişsel faktörler arasındaki karşılıklı ilişkileri incelemek için hem nitel içgörüleri hem de nicel titizliği entegre etmektedir. Veriler, Türkiye genelinde termal otellerde kalan 458 müşteriden toplanmıştır. Analiz, önerilen hipotezlerin sağlam ve çok boyutlu bir değerlendirmesine olanak sağlayan bulanık kümeli Nitel Karşılaştırmalı Analiz (fsQCA) ile birlikte Kısmi En Küçük Kareler Yapısal Eşitlik Modellemesi (PLS-SEM) kullanılarak yürütülmüştür. PLS-SEM'den elde edilen bulgular, yenilik ve memnuniyetin tüketicilerin servis robotlarını kabulü üzerinde istatistiksel olarak anlamlı pozitif bir etkiye sahip olduğunu, keyif ve olumsuz duygu etkilerinin ise anlamsız olduğunu göstermektedir. Ancak fsQCA sonuçları, tek başına bireysel faktörlerden ziyade belirli duygusal durum kombinasyonlarının daha yüksek kabul seviyelerine etkili bir şekilde yol açabileceğini ortaya koymuştur. Bu bulgular, konaklama ortamlarında hizmet robotu uygulama stratejilerini geliştirmek için değerli çıkarımlar sunmaktadır.

Anahtar Kelimeler: fsQCA, İnsan-robot etkileşimi, Otelcilik sektörü, PLS-SEM, Teknoloji benimseme

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INTRODUCTION

Service robots have become integral across a wide range of industries, including hospitality, healthcare and aged care. This rise is attributed to remarkable advancements in automation technologies. This is also reflected in the market projections. In fact, Fu et al. (2022) forecasted that by 2027, the service robotics market will reach an estimated value of US $41.49 billion. Tziolas et al. (2023) argued that cost-effectiveness of the service robots is the major reason behind this increased attention. Moreover, the Covid-19 pandemic further accelerated the use of service robots as it helped in decreasing the interactions between people (Chi et al., 2020).

The emergence of service robots has resulted in an increasing body of literature examining consumer reactions (Kim et al., 2022). At the heart of these studies, consumer acceptance is considered a focal point (Kim et al., 2022). Here, acceptance is defined as encompassing consumers' willingness and intention to use service robots and based on this, it serves as a pivotal investment decision factor for hospitality enterprises (Schepers et al., 2022). Despite the steps taken by scholars to understand consumer acceptance, it is still believed that gaps persist, especially regarding the interplay between cognition and emotion in shaping consumer behavior (Khoa et al., 2023). According to Gursoy et al. (2019), consumer emotions have considerable influence. Neglecting this dual impact could lead to misconstrued perceptions of consumer behavior in automated service settings.

This study aims to address this research gap by providing an in-depth examination of how specific cognitive and affective factors determine consumer reactions to service robots. The findings demonstrate the relative influence of both cognitive and emotional variables on key outcome variables, such as intention to use, satisfaction, and recommendation behavior. By investigating actual consumer experiences through direct interaction, this study generates insights grounded in real-world data. The choice of variables is informed by consumer perspectives rather than theoretical assumptions alone. This dual perspective, combining cognition and emotion, fills an important gap in literature and integrates two previously disconnected areas of research. The novel framework and empirical approach advance theoretical knowledge of human-robot interactions in services. They also offer valuable practical insights to hospitality businesses regarding the adoption and implementation of service robots.

In the realm of automated service settings, the relationship between cognition and emotion in influencing consumer behavior towards service robots has emerged as a critical research gap. Specifically, there remains a notable lack of comprehensive investigation into how cognitive and affective factors jointly shape consumer reactions and behavior in this context. The existing literature has predominantly focused on cognitive acceptance factors, such as perceived usefulness, perceived ease of use, and trust in technology. While crucial, they represent only one facet of consumer response. Conversely, the emotional dimension of consumer responses has been largely overlooked. Feelings of comfort, anxiety or satisfaction in interacting with service robots play an equally pivotal role in shaping overall consumer attitudes and behaviors. Understanding consumer behavior requires direct observation and interaction. Consumers who have first-hand experience with service robots offer valuable insights that go beyond theoretical assumptions. The variables selected for this study were based on real-world data, ensuring that the findings are applicable in practical settings and offer actionable insights for businesses and policymakers.

1. Theoretical Background

1.1 Service Robots in Global Hospitality

This research explores various aspects of how consumers interact with service robots, focusing particularly on the elements that shape their willingness to adopt such technologies. Building on the conceptualization of Gursoy et al. (2019), consumer acceptance is understood here as a behavioral tendency to engage with service robots. Although acceptance can be approached from several perspectives, the present study highlights the consumer's perspective viewpoint (Ayyildiz et al., 2022).

In recent years, scholars have expanded traditional frameworks by integrating them with complementary theories and constructs. For example, Shu and Ye (2023) combined Technology Acceptance Model (TAM) (Davis, 1989) with privacy calculus theory. In this integrated model, scholars added "personal innovativeness" as one of the main determinants for adoption of robots in the hospitality sector.

Recognizing the limitations of traditional models, a second stream of research has emerged that focuses on the development of novel theoretical frameworks (Tussyadiah & Park, 2018). Two of the most frequently cited frameworks are the Artificial Intelligent Device Use Acceptance (AIDUA) model proposed by Gursoy et al. (2019) and the Service Robot Acceptance Model (sRAM) formulated by Wirtz et al. (2018). Both frameworks provide structured explanations for understanding consumer adoption of service robots.

In addition to these models, alternative theoretical perspectives have been employed, including Attribution Theory (AT) (Kelley & Michela, 1980), Construal Level Theory (CLT) (Trope and Liberman, 2012), Social Exchange Theory (SET) (Cook et al., 2013), the Stereotype Content Model (Canton et al., 2023), and Psychological Ownership Theory (Asatryan & Oh, 2008). Each perspective offers unique insights into the multifaceted nature of consumer interactions with service robots.

Despite significant strides in understanding customer acceptance of service robots, notable gaps remain in the existing body of research. Earlier research has largely concentrated on functional benefits and anthropomorphic features of service robots, which may have resulted in overlooking other important viewpoints (Lu et al., 2020). In addition, the psychological outcomes of customer–robot interactions remain insufficiently addressed, especially regarding the role of emotions in shaping users' intentions and subsequent behaviors (Seo & Lee, 2021).

1.2 Theoretical Frameworks for Technology Acceptance

The integration of robots into various service industries has become increasingly prevalent. From automated customer service assistants to robotic baristas, these technological advancements are reshaping the way people interact with services. However, beyond the functionality and efficiency of these robots lies a critical factor: their emotional impact on consumers. Understanding how positive and negative emotions influence consumer acceptance of service robots is crucial for their successful implementation and widespread adoption (Canton et al., 2023).

Positive affect or the experience of positive emotions has long been recognized as a driving force behind consumer behavior. When consumers feel joy, excitement, or satisfaction during their interactions with service robots, their acceptance of this technology is significantly enhanced. Research by Ajina et al. (2023) highlights that positive affect serves as a strong predictor of customer technology acceptance. One of the key factors contributing to positive affect is the enjoyment derived from these interactions. As noted by Won et al. (2023), consumer acceptance of technology is closely tied to the level of enjoyment experienced. Service robots designed to provide delightful experiences, through personalized interactions or entertaining features, are more likely to evoke positive emotions in consumers. When consumers derive pleasure from their interactions with service robots, it further influences their acceptance. Novelty, characterized by experiences of surprise and the "wow effect," is closely tied to emotional experience. It has been identified as a driving force behind the intention to adopt new technologies (Chirico & Gaggioli, 2023).

Conversely, negative affect, encompassing emotions such as frustration, disappointment, or fear, can hinder consumer acceptance of service robots. When consumers experience negative emotions during their interactions, it can lead to skepticism, distrust, and even avoidance of technology (Rosete et al., 2020).

Positive affect has been identified as a strong predictor of customer technology acceptance (Ajina et al., 2023). When consumers experience positive emotions during their interactions with service robots, their intention to use them increases significantly. In contrast, negative affect often arises from consumers' cognitive appraisal of service robots. Factors such as perceived usability issues, concerns about privacy and security, or fear of job displacement can trigger negative emotions. Huang et al. (2023) emphasize the importance of addressing these concerns to mitigate the impact of negative affect on consumer behavior. Understanding how negative affect impact consumer behavior is crucial for the successful implementation of service robots.

While existing literature provides valuable insights there remains a theoretical gap that warrants exploration (McCartney & McCartney, 2020). Much of the current research focuses on descriptive analyses of consumer behavior, without delving deeply into the underlying psychological mechanisms driving these emotions (Asatryan & Oh, 2008; Seo & Lee, 2021; Tuomi et al., 2021; Venkatesh, 2000).

To truly understand the impact of positive and negative affect on consumer acceptance, future research should aim to unravel the emotional dynamics at play (Ou & Verhoef, 2017). This involves exploring the cognitive processes underlying consumers' emotional responses to service robots, as well as identifying effective strategies for managing and influencing these emotions. Drawing on theories from psychology and behavioral economics can provide a deeper understanding of how emotions shape behavior (Cohen et al., 2018). By integrating concepts such as emotional regulation, cognitive appraisal theory and prospect theory, researchers can uncover nuanced insights into the emotional drivers of consumer acceptance.

The integration of service robots into various industries had profound implications for consumer behavior (Seo & Lee, 2021). Understanding the emotional impact of these interactions, particularly the effects of positive and negative affect, is essential to ensuring the successful adoption of this technology (Huang et al., 2023). While positive affect can enhance consumer acceptance, negative affect poses significant challenges that must be addressed (Won et al., 2023). Moving forward, bridging the theoretical gap through in-depth research into the emotional dynamics of consumer interactions with service robots will pave the way for more effective implementation strategies. Based on this discussion, the following hypothesis and research model (see Figure 1) are proposed in this study:

H1. When consumers experience enjoyment, their willingness to use service robots is likely to increase.

H2. Higher levels of negative affect among consumers are expected to reduce their intention to adopt service robots.

H3. Novelty has a positive effect on consumers' intention to use service robots.

H4. Satisfaction has a positive effect on consumers' intention to use service robots.

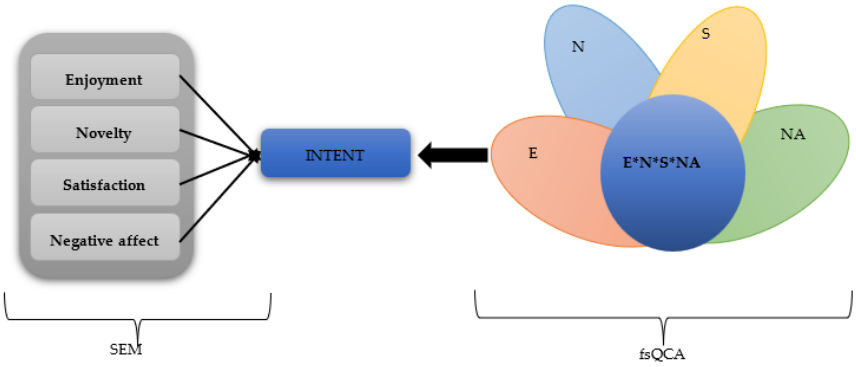

Figure 1. Proposed Configuration Model

2. Materials and Methods

In this study, a survey was carried out to explore how consumers perceive the integration of service robots in thermal hotels. The survey employed a structured a questionnaire adapted from validated scales used in previous studies. It covered a range of aspects, including sociodemographic characteristics of consumers and their evaluations of thermal hotels. The sociodemographic section of the questionnaire included items such as age, gender, educational background, marital status, and length of their stay in thermal hotels. Moreover, participants' positive and negative emotions toward thermal hotels, along with their intention to adopt service robots, were measured using a five -point Likert scale.

2.1 Research Design

The study employed a purposive sampling method to collect from consumers, targeting individuals who met specific inclusion criteria relevant to the research objectives (Lim & Ting, 2012). The population of interest consisted of customers who visit and stay at thermal hotels. To mitigate potential biases associated with non-random sampling, the questionnaire was administered at randomly selected thermal hotels across Türkiye on different days and at various times.

A total of 600 questionnaires were distributed; however, only 458 were fully completed and returned. Additionally, eight questionnaires were identified as incomplete and subsequently excluded from the analysis, resulting in a final sample size of 458 respondents.

PLS-SEM and fsQCA were used to study the acceptance of service robots intended for use in thermal hotels. Both methods provide comprehensive insights by identifying adequate causal configurations of antecedents that determine outcomes. Previous research on tourist experiences (Kumar et al., 2023) has applied methods such as fsQCA to identify significant heterogeneity among participants by analyzing their positive and negative perceptions. PLS-SEM was chosen for this study because it offers a unique structure score that allows for the application of fsQCA (Rasoolimanesh et al., 2023). Based on the study by Becker et al. (2023), Partial Least Squares Structural Equation Modeling (PLS-SEM) is a combination of explanatory and predictive analytics owing to its causal nature. This is pertinent to contemporary hospitality and tourism research, which requires scientifically backed hypotheses to

steer managerial recommendations. PLS-SEM is an appropriate methodology for both exploratory and confirmatory studies (Hair & Alamer, 2022). The use of fsQCA with PLS-SEM in this study enhances the results by effectively configuring antecedents for random combinations, given its predictive nature (Kumar et al., 2023). This is because of the proximity and asymmetrical assumptions between the independent and dependent variables made by the fsQCA (Rasoolimanesh et al., 2023).

Ragin (2014) popularized Qualitative Comparative Analysis (QCA), which has been widely recognized and applied across diverse domains (Zhang & Zhang, 2021). Because of its potential to reveal intricate causal relationships, QCA was deemed appropriate for this study's objectives. QCA allows for the analysis of how multiple conditions can interact to cause an outcome, revealing different pathways rather than simple single-factor effects. This configurational approach reflects the diverse and overlapping influences that shape tourism entrepreneurship. Additionally, QCA's set-theoretic foundation enables the identification of conditions that are sufficiently or necessarily linked to the outcomes.

3. Results

The two-stage PLS-SEM method, which consists of measurement and structural model evaluation, was implemented to substantiate and confirm the structure of the created model (Hair & Alamer, 2022). According to Table 1, all loading factors exceed 0.7, Average Variance Extracted (AVE) values exceed the recommended cut-off value of 0.5, and the Composite Reliability (CR) and rho_A values exceed 0.7 (Hair & Alamer, 2022).

Table 1. Results of Model Assessment

Item	OL	CA)	rho_a	CR	AVE
Positive Affect (PA)					
Enjoyment (Venkatesh, 2000)					
PA1	0.819	0.953	0.954	0.953	0.771
PA2	0.883				
PA3	0.841				
PA4	0.876				
PA5	0.920				
PA6	0.926				
Novelty (N) (Kim et al., 2022)					
N1	0.964	0.961	0.961	0.961	0.859
N2	0.923				
N3	0.895				
N4	0.924				
Satisfaction (S) (Tussyadiah & Park, 2018)					
S1	0.873	0.942	0.944	0.942	0.803
S2	0.914				
S3	0.939				
S4	0.857				
Negative affect (NA)					
NA1	0.847	0.938	0.945	0.936	0.748
NA2	0.889				
NA3	0.704				
NA4	0.867				
NA5	0.993				

Consumers' intentions to use service robots (I) (Wirtz et al., 2018)					
I1	0.957	0.965	0.965	0.965	0.872
I2	0.946				
I3	0.920				
I4	0.913				

Note. OL = Outer Loading; CA = Cronbach's Alpha; ρ_A = Rho_A; CR = Composite Reliability; AVE = Average Variance Extracted. All values are above the recommended thresholds (Hair & Alamer, 2021).

Discriminant validity was assessed using the Heterotrait-Monotrait Ratio (HTMT), Fornell-Larcker, and Cross-Loading analyses. All HTMT values were below the recommended cut-off value (0.9) (Hair & Alamer, 2022), demonstrating an acceptable level of discrimination for the proposed model. See Table 2 for details.

Table 2. Results of Discriminant Validity

	Enjoyment	Intention	Negative Affect	Novelty	Satisfaction
HTMT Ration					
Enjoyment					
Intention	0.787				
Negative Affect	0.761	0.683			
Novelty	0.751	0.752	0.601		
Satisfaction	0.890	0.819	0.764	0.733	
Fornell Larcker					
Enjoyment	**0.878**				
Intention	0.787	**0.934**			
Negative Affect	0.766	0.689	**0.865**		
Novelty	0.752	0.753	0.607	**0.927**	
Satisfaction	0.889	0.819	0.766	0.733	**0.896**

3.1 Assessment of Model Using PLS-SEM

Prior to conducting the model tests, it was imperative to evaluate the fit indices. To determine the misfit in the observed correlations, the Standardized Root Mean Square Residual (SRMR) was utilized, with a recommended threshold value of less than 0.08 as per Hu and Bentler (1998). The proposed model's improved fit in the χ^2 value was measured using another fit index, the Normed Fit Index (NFI). Upon analyzing the fit indices in this research (SRMR = 0.037, d_ULS = 0.377, d_G = 0.636, χ^2 = 1,752,004, NFI = 0.870), it was concluded that all values suggested a satisfactory fit.

Table 3. PLS-SEM Results

	HYPOTHESES	β	M	2.5%	97.5%	Bias	STDEV	f^2	t	p	Result
H1	Enjoyment -> Intention	0.099	0.097	-0.134	0.318	-0.002	0.115	0.006	0.866	0.387	✗
H2	Negative Affect -> Intention	0.094	0.098	-0.037	0.237	0.004	0.070	0.013	1.348	0.178	✗
H3	Novelty -> Intention	0.299	0.304	0.179	0.439	0.005	0.066	0.136	4.537	p < .001	✓
H4	Satisfaction -> Intention	0.438	0.433	0.235	0.632	-0.005	0.102	0.130	4.307	p < .001	✓

The predictive power of the structural model was evaluated using the R^2 and Q^2 values. Accordingly, the R^2 values indicate that the structural model possesses ample predictive capability (Hair & Alamer,

2022). Path coefficients (β) determined the strength of the relationships in the model, while effect size (f^2) established the amount of variance explained by the variables.

The significance of the path coefficients was evaluated using the bootstrap method with 5000 subsamples. The predictive efficacy of the model was assessed using R^2 values. The importance of the variables was determined using the f2 values. A blinded analysis was performed to calculate the Q^2 index; a positive Q^2 in the outcome variables indicated the model's predictive ability. In addition, a novel CVPAT method was employed. The superior predictive power of the model was confirmed by comparing the mean error to PLS-SEM, mean index, and linear models. If the average error is lower and statistically significant compared with the other methods, it implies that the model has strong predictive capabilities.

Based on the path analysis results shown in Table 3, there was no significant and positive influence of enjoyment and negative affect on consumers' intention to use service robots. As a result, hypotheses H1 and H2 were not supported. However, satisfaction and novelty have a significant positive influence on consumers' intentions to use service robots. Therefore, Hypotheses H3 and H4 were supported.

3.2 Assessment of Model Using FsQCA Analysis

Evaluation of the model using fsQCA: The fuzzy set qualitative comparative analysis (fsQCA) method was used to test the model and assess its robustness. fsQCA is a qualitative comparative approach that allows the examination of combinations of independent variables and their effects on dependent variable outcomes. The observation units in the dataset were defined as fuzzy sets, with membership degrees ranging from 0 to 1. As a result of the analysis, the effects of different combinations of variables that make up the model on the dependent variable were examined. The results demonstrate the validity of the model and its explanatory capability under different conditions. The tests performed with fsQCA revealed that the model was consistent and well founded.

Table 4. Sufficient Causal Configurations

Pahts	Enjoyment	Novelty	Negative Affect	Satisfaction	Raw Coverage	Consistency
~E*N*NA	~	●	●	~	0.683	0.863
E*~N*~S	●	~	~	~	0.693	0.855
E*N*S*~NA	●			●	0.432	0.990
Solution Coverage				0.712		
Solution Consistency				0.835		

fsQCA analysis followed the steps recommended by Rasoolimanesh et al. (2023). Initially, PLS-SEM was used to obtain all construct scores, which were then calibrated between 0-1 in the fsQCA software package. Scores of 0 were assigned 0.5, scores of -3 or less were assigned a value of 0, and scores of 3 or more were assigned 1, thereby creating the "fuzzy sets." Subsequently, truth tables were constructed to examine all possible configurations. Rows that had two or fewer cases and consistency values below 0.80 were disregarded based on prior research recommendations. An intermediate solution was applied to calculate consistency scores for the configurations, following the guidance of Maggetti and Levi-Faur (2013). All probable configurations were examined to determine the consistency and coverage scores. Configurations with consistency above 0.80 and coverage above 0.20 was deemed adequate. fsQCA is an asymmetrical approach that enables the evaluation of the model through a qualitative comparative analysis.

The fsQCA results indicated that a diverse combination of positive and negative affect can lead to increased general intentions to use robots. All three cases produced high results owing to the various configurations formed, surpassing those obtained from PLS-SEM (refer to Table 4). Novelty and negative affect are crucial in Configuration 1. In contrast, Configuration 2 exhibits elevated levels of enjoyment. Configuration 3, on the other hand, shows a high level of negative affect enjoyment, whereas novelty and satisfaction indicate low levels of negative affect. Therefore, when travelers simultaneously rate high levels of enjoyment, novelty, negative affect, and satisfaction, their levels of satisfaction, repurchase intention, and word-of-mouth will increase. The data showed patterns indicating high enjoyment levels and low levels of negative affect and satisfaction, along with low levels of hospitality, interaction, knowledge, and memorability experiences.

3.3 Necessary Conditions Analysis

The analysis of necessary conditions revealed that no single condition met the strict necessity criterion (consistency > 0.9). However, novelty approached this threshold with a consistency value of 0.87 and coverage of 0.79, suggesting its importance across most cases of high intention to use service robots. The absence of negative affect also showed relatively high consistency (0.83) and coverage (0.76), indicating its relevance as a quasi-necessary condition (Figure 2).

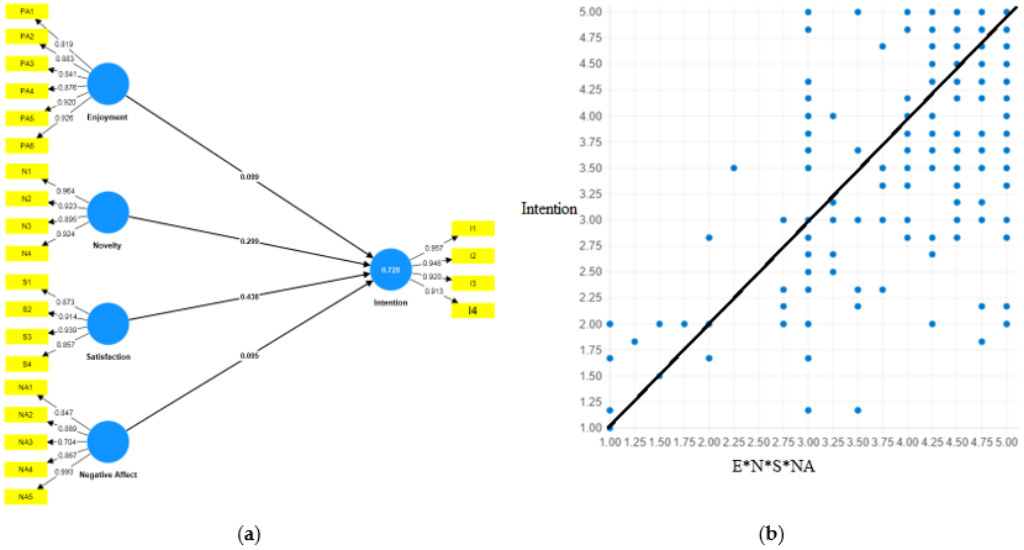

Figure 2. (a) Results of the Research Model; (b) Configuration 3 Intentions to Use Service Robots

4. Discussion

This study investigated consumer attitudes towards the adoption of service robots in thermal hotels. It examined four hypotheses: H1 predicts that enjoyment influences the intention to use service robots. However, PLS-SEM results showed that this effect was not statistically significant. H2 suggests that negative affect affects the intention to use service robots. However, this analysis did not yield a statistically significant effect. H3 posited a positive impact of the novelty factor on acceptance, which was confirmed by the test. H4 predicted a positive effect of satisfaction on acceptance and the analysis result supported this prediction. The fuzzy set method findings revealed that varying combinations of emotion increased the acceptance of service robots. Therefore, this research examined the factors affecting acceptance and tested the hypotheses in line with the study's goal.

This study indicates that service robots are significant in eliciting positive emotions and reducing negative emotions in consumers. Moreover, utilitarian aspects, such as functionality, proved vital in promoting positive emotions. Insignificant affect were found regarding the impact of interactivity on positive affect, aligning with the results of Fernandes and Oliveira (2021). Interestingly, the results also

indicated that interactions between consumers and robots could lead to negative emotional responses. Interesting outcome can be explained through lessen human touches in the service (Mori et al., 2012). Consequently, observing negative affect in human-robot encounters is plausible. Notably, the finding that a negative emotional state can have a positive impact on the consumers' intention to use service contradicts previous research (Jung & Yoon, 2011). There are possible explanations for this. First, consumers may be able to manage the negative effects of interacting with service robots, allowing them to accept the robots despite experiencing negative emotions.

In the realm of artificial intelligence (AI) and robotic technologies, understanding consumers' intentions to engage with service robots is paramount. This article delves into the theoretical and methodological contributions of a study focused on unraveling the complexities surrounding consumers' acceptance of service robots in thermal hotels. By integrating human, technological, and consumer characteristics, this study sheds light on the multifaceted factors influencing consumer behavior in this domain.

Emotions play a pivotal role in shaping individuals' attitudes and behaviors towards technology, including service robots. The study underscores the significance of emotional factors such as enjoyment, negative affect, novelty and satisfaction in influencing consumers' acceptance of service robots. Contrary to conventional wisdom, it reveals that service robots have the capacity to evoke positive emotions and alleviate negative ones. Furthermore, the functionality of robots emerges as a critical determinant in fostering positive emotions among users.

An intriguing finding of the study pertains to the impact of interaction on consumer emotions. Unlike conventional assumptions, the study indicates that the effect of interaction on positive emotion is negligible, echoing previous research on digital voice assistants. Surprisingly, interactions with service robots were also found to elicit negative emotions. This unexpected outcome challenges existing paradigms and underscores the need for nuanced examinations of human-robot interactions. This departure from conventional understandings of human-human interaction dynamics highlights the unique dynamics of human-robot interactions. By elucidating the role of negative emotions in shaping consumer behavior, the study opens new avenues for understanding and leveraging emotional responses in technology adoption contexts.

Conducting this study contributes to previous research that primarily utilized PLS-SEM to investigate the balanced relationships between the factors related to robot adoption (e.g., Lu et al., 2019). By adopting an asymmetrical approach, the study unveils the nuanced configurations of factors that influence consumer behavior in this domain. While the study offers valuable insights into consumers' intention to use service robots, notable gaps in theoretical discourse remain. Specifically, the absence of a robust theoretical discussion and the lack of identification of theoretical gaps underscores the need for more comprehensive examinations of the underlying mechanisms driving consumer behavior in human-robot interaction contexts. Future research should strive to address these gaps by integrating diverse theoretical perspectives and adopting interdisciplinary approaches.

The theoretical and methodological contributions of this study represent a significant step forward in understanding consumers' intention to use service robots. By unraveling the complexities of human-robot interactions and leveraging innovative analytical techniques, the study enriches the theoretical understanding of technology adoption processes. Moving forward, addressing theoretical gaps and embracing interdisciplinary approaches will be crucial in advancing knowledge in this burgeoning field.

CONCLUSION AND RECOMMENDATIONS

Thermal hotel businesses should design customer-service robot interactions that simplify process and create positive experiences. The functionality and usefulness of robots should be emphasized. To reduce the complexity of using robots, companies should strike a balance between their appearance and behavior, avoiding an excessive number of human-like features. Staff should receive training to alleviate negative emotions and address concerns about privacy and security. Service robot applications should be introduced gradually, incorporating consumer feedback for continuous improvement. Robot adaptability and personalization should cater to the diverse needs of different customer segments.

Thermal hotel businesses can gain practical benefits from robotic applications. Reception robots can accelerate registration processes and reduce customer waiting times, thereby increasing satisfaction and productivity. Room-cleaning robots can ease staff workload, enabling more rooms to be serviced and increasing guest capacity. Restaurant and dining robots can handle tasks such as menu services, order taking, and food delivery, reducing the need for human personnel while enhancing speed and service quality. Guidance robots can provide in-hotel directions, information and recommendations, assisting guests more efficiently. By employing robots in treatment areas, staff workload can be reduced, allowing more patients to be cared for and ultimately enhancing treatment quality and efficiency. The use of guide robots for out-of-hotel activities and excursions, automaton of room controls such as ventilation, heating-cooling, and lighting, and offering bellbot (robotic bellboy), valet, and baggage handling services, can all further enhance service quality. Robots can also conduct surveys on customer satisfaction. In summary, the use of robots increases both comfort and quality for guests. Consequently, hotel businesses can enhance productivity and overall service quality by integrating robots across various operations, thereby gaining a competitive advantage.

This study examined the factors that influence the acceptance of service robots in thermal hotels. However, some limitations be noted. The demographic diversity was limited, as only staying customers were included. The sample was confined to thermal hotels in Türkiye, which may restrict generalizability to other countries. Although only five independent variables were analyzed, broader emotions, attitudes, and behaviors could have been included. Incorporating in-depth qualitative data alongside the survey could strengthen the model.

Future research should addressed these limitations. Comparative studies across countries and cultures could test the universality of the findings. Research evaluating the opinions of hotel employees and managers would also be valuable. Longitudinal studies could measure long-term effects and sustainability of robotic implementation. Separate modeling for different types of hotels and accommodation could be conducted and mixed-methods studies incorporating qualitative approaches can provide a more comprehensive understanding. These findings offer important insights for hotel businesses seeking to implement service robots effectively.

Compliance with Ethical Standards

Conflict of Interest Declaration: *The author declares that he does not have a conflict of interest with other third parties and institutions, or if so, how this conflict of interest arose and will be resolved, and author contribution declaration forms are added to the article process files with wet signatures*

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