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The Age of Artificial Intelligence: The Effect of Technology-Organization-Environment on Intention to Adopt Robotic Technologies in Hotel Businesses

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Abstract: This study examines the factors influencing hotel managers' intentions to adopt robotic technologies in the hotel industry. A questionnaire-based survey was conducted among hotel managers in Afyonkarahisar, Antalya, and Izmir Provinces. The survey collected data from 396 participants. The collected data were then analyzed using PLS-SEM to identify the relationships between the factors and adoption intentions. The analysis revealed that technology and organization significantly influence the intention to adopt robotic technologies in hotels. However, the environmental factor was found to have no significant effect on adoption intentions. Understanding the factors that drive adoption intentions can guide the development of effective strategies for implementing robotic technologies in hotels, leading to increased operational efficiency and improved guest experiences. This research contributes to the existing literature by applying the TOE framework to examine the adoption of robotic technologies, specifically in the hotel industry. The IPMA used in this study provides a unique perspective on the relative importance and performance of the influencing factors, which aids in the decision-making process.

Keywords: adoption intention, artificial intelligence, robotics, technology-organization-environment, tourism.

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INTRODUCTION

In recent years, the rapid development of robotics and artificial intelligence has profoundly impacted various aspects of human life (Nabila et al., 2021). Robots With their ability to mimic human actions and perform complex tasks autonomously, robots found applications in multiple sectors, including accommodation and tourism (Samala et al., 2020). The adoption of robotic technologies is projected to contribute approximately 15.7 trillion dollars to the world economy by 2030, driven by 6.6 trillion dollars from productivity growth and 9.1 trillion dollars from consumption (Engel & Dahlhaus, 2021). However, despite increasing investments in information technology, the implementation and adoption of robotics in various industries remain a topic of academic debate among stakeholders, including managers and decision-makers (Massaro et al., 2021; Leesakul et al., 2022; Menaouer et al., 2022).

Existing research has primarily focused on user adoption of technology using traditional models such as the Reasoned Action Theory (RAT) (Ajzen & Fishbein, 1980), Technology Acceptance Model (TAM) (Davis, 1989), and Innovation Diffusion Theory (IDT). However, little attention has been given to understanding the perspectives of managers and decision-makers. Hence, it is crucial to examine the adoption behaviors of hotel managers regarding robots and robotic technologies within the Technology-Organization-Environment (TOE) framework proposed by Tornatzky et al. (1990). By investigating the effects of technological, organizational, and environmental factors on hotel managers' intentions to adopt robotic technologies, this research aims to fill the gap in the literature and provide valuable insights to decision-makers.

The accommodation and tourism sectors have increasingly adopted robots due to their numerous advantages. These benefits include providing fast and accurate service to guests, reducing staff workload, and conserving labor resources (Vatan & Dogan, 2021). Additionally, integrating robotic technologies into the tourism industry has proven crucial for advancing sustainability efforts. This becomes particularly significant in exceptional situations like pandemics, where robots can play a vital role in cleaning, disinfecting, and maintaining hygiene at sites, thereby minimizing the risk of infection for both staff and guests. This ensures a safer and more reassuring lodging experience (Gaur et al., 2021). However, despite these advantages, there are several barriers that hinder the widespread adoption and implementation of robots in the hospitality industry. These obstacles include high costs, reluctance from staff and guests, and technological challenges (Gaur et al., 2021).

In recent years, the tourism sector has undergone a radical transformation due to technological innovations. These advancements, particularly the development of robotic systems, have significantly changed tourism businesses' structure, service delivery, and cost structures (Buhalis et al., 2020). This revolution has led to a fundamental restructuring of accommodation services. Additionally, the Internet of Things has enhanced travelers' access to personalized devices and systems, leading to a rise in intelligent ecosystems within the tourism industry (Gretzel et al., 2015). It is crucial to acknowledge that these changes are not evolutionary but revolutionary. This has given rise to the concept of smart hospitality and integrating all internal and external processes within the framework of ambient intelligence tourism (Jones et al., 2017; Parida et al., 2021).

In the competitive market, organizations use different technologies. However, the technologies used within their internal processes also play an essential role and form the technological context of the TOE (Technological, Organizational, and Environmental) framework. The diffusion process involves reducing uncertainty, where innovations have characteristics such as relative advantage, compatibility, complexity, trialability, and observability. Tornatzky & Klein (1982) identified five additional characteristics: cost, communicability, divisibility, profitability, and social acceptability. The concept of "relative advantage" refers to the perceived superiority of a new technology or innovation over an existing one. This concept has been explored in several studies in different contexts. For example, Cabral & Jabbour (2020) used the TOE and human-organization-environment (HOE) frameworks to assess the impact of big data on firm performance in the hospitality industry.

By incorporating the Unified Theory of Acceptance and Use of Technology (UTAUT) framework into the TOE framework, Awa et al. (2017) complemented organizational-level technology adoption with user-level adoption. Their study considered the technological characteristics of the TOE framework, organizational factors, environmental influences, and user-level factors. The combined TOE and UTAUT frameworks effectively addressed the organizational-level effects of technology adoption and use and the user-level adoption factors. A literature review on the importance of compatibility in adopting innovations reveals that compatibility refers to the extent to which adopting new technologies is consistent with existing values, needs, and prior experiences. In this context, compatibility, which encompasses technological and organizational environmental characteristics, helps overcome barriers to adoption.

The perceived cost has been highlighted as essential in adopting robotic technologies. People are less likely to adopt robotic technologies if the perceived costs outweigh the benefits. Therefore, organizations need to consider the perceived costs' negative impact when adopting robotic technologies. In addition, ensuring compatibility throughout the adoption process is critical. Aligning a new robotic technology with existing values, needs, and prior experiences facilitates its use and removes barriers (Lee et al., 2021).

The consistent and seamless integration of robot applications in hotel businesses can enhance efficiency and improve the customer experience. Therefore, before incorporating robots into hotel operations, evaluate their compatibility with the hotel's existing values, practices, and information technology infrastructure (Xu et al., 2020). The compatibility of robots with the hotel's established values is crucial for maintaining the hotel's brand image. Ensuring consistency in using robot applications throughout the hotel is also essential. For example, if a robot is employed in the reception department, similar robots should be utilized in other departments to maintain a consistent guest experience. Integrating robots with the hotel's information technology applications enhances their functionality and efficiency. For instance, integrating them with the hotel reservation system can streamline the check.

The adoption of robotic applications in the hotel sector not only improves customer service but also increases the profitability of hotel businesses (Ivanov & Webster, 2019; McCartney & McCartney, 2020). By using robots, businesses can reduce labor costs while increasing service quality and efficiency, resulting in higher customer satisfaction and loyalty. This, in turn, allows hotel companies to expand their market share and profitability through increased repeat business. While robotics technology offers numerous benefits to hotel companies (Pizam et al., 2022), its implementation also presents challenges. Therefore, companies must develop a well-defined strategy and ensure proper execution before transitioning to robotic technology.

Indeed, mastering the operation of robotic applications can be a complex process, especially for individuals with a technical background. The development of robotic applications requires expertise in various fields, such as mechanics, electronics, and software development (Ameen et al., 2021). Implementing these applications also presents challenges. Beyond the intricacies of the development phase, real-world deployment depends on several factors, including the physical conditions of the operational environment, user requirements, and seamless integration of the application (Adam & Alhassan, 2021). In addition, integrating robotic applications into existing business systems can be a daunting task. Although robots offer benefits in various areas of the hospitality industry, successful integration requires careful consideration of compatibility with the hotel's values, practices, and infrastructure. In this way, robotic integration can align with the hotel's brand image and maintain consistency in the guest experience.

To overcome these barriers and promote the successful integration of robotic technologies, it is essential to identify and understand the various technological, organizational, and environmental factors that influence hotel managers' intentions. The proposed study offers an invaluable organizational perspective on the decision-making processes involved in adopting hotel robots. By exploring the factors that influence the adoption and implementation of robotic technologies in the hospitality industry, this research aims to provide critical insights for decision-makers. These insights will not only shed light on the barriers and opportunities for robot adoption in hotels but also enable decision-makers to make informed choices when implementing these technologies. Moreover, the study's findings are expected to promote sustainable development within the tourism sector. This research can lead to positive change in the industry by identifying ways robotic technologies can enhance operational efficiency and contribute to environmental and social sustainability.

The significance of this study extends beyond the hospitality industry. By utilizing the well-established TOE framework, this research aims to provide broader insights into how the framework can be applied in the service sector, particularly concerning emerging technologies. Such insights will be valuable to researchers and practitioners seeking to understand the dynamics of technology adoption and the organizational factors that influence decision-making processes.

METHODS

The mentioned text seems to describe the methodology and data analysis process of a study related to the adoption of robotic technologies by hotel managers in certain provinces. The researchers used existing scales for their questionnaire and conducted a pilot test to ensure clarity and completeness. The study aimed to determine the impact of technology, organization, and environment (TOE) factors on hotel managers' intention to adopt robotic technologies in their hotels. To collect data, the researchers used a convenience sampling method by distributing the questionnaire online to hotel managers in the provinces of Afyonkarahisar, Antalya, and Izmir. The data collection period was from May 5 to October 25, 2022, resulting in 396 usable responses for analysis.

The researchers used a standard two-step approach for data analysis. First, a confirmatory factor analysis (CFA) was conducted to assess the validity of the measurement scales. Second, structural equation modeling (SEM) was used to test the study hypotheses. Partial Least Squares Structural Equation Modeling (PLS-SEM), a commonly used method in tourism sector research, was used for data analysis. PLS-SEM was preferred because of its flexibility in model analysis and its ability to handle non-normally distributed data. The Smart PLS program was chosen for the analysis due to the reflective nature of the scales. The analysis consisted of three steps. The first stage evaluated the measurement model by calculating the reliability (α) and validity of the scales. The second stage focused on the evaluation of the structural model. Finally, in the third stage, structural equation modeling was used to test the hypotheses of the study.

RESULTS AND DISCUSSION

SEM research is generally based on maximum likelihood estimation, assuming the data collected follow a multivariate normal distribution. In order to evaluate this assumption, the kurtosis and skewness coefficients of the data were calculated using SPSS and Smart PLS software, as suggested by Hair et al. (2022). This analysis showed that the examined data met the multivariate normality requirement, and the kurtosis and skewness coefficients were within the acceptable range of –1.5 to +1.5. To further verify the normality assumption, the Mardia normality test was performed. This test showed that the data had multivariate skewness ($\beta = 4.204$; $p > 0.01$) and multivariate kurtosis ($\beta = 61.105$; $p > 0.05$) values and that the data were normally distributed.

In terms of the demographic and individual characteristics of the participants, the results showed that approximately 55% were male, and 45% were female. 41% of the participants were between 36 and 55 years old, and 22% had bachelor's degrees. Approximately 30% of the participants have 4–7 years of experience in the hospitality industry, and 21% have 8–11 years of experience. 18% of the participants have 4–7 years of management experience in the hospitality sector. About 15 percent of hotels have 51–150 full-time employees, and about 25 percent have 51–200 rooms. Most hotels (40%) are in holiday resorts. 52% of the hotels have mainly foreign guests, and 48% have domestic guests on holiday. Approximately 35% of the hotels have operated for 15–26 years. Finally, 35% of the hotels were part of an independent chain and were institutionally owned and managed.

Table 1 Confirmatory Tetrad Analysis Results

Indicators	β	X¯	S.d	t	p	CI low adj.	CI up adj.	F/R
1: T1,T2,T3,T4	0.075	0.075	0.077	0.982	0.326	–0.103	0.253	R
4: T1,T2,T3,T5	0.085	0.085	0.064	1.326	0.185	-0.064	0.236	R
1: E1,E2,E3,T1	0.115	0.113	0.076	1.502	0.133	-0.034	0.266	R
2: E1,E2,T1,E3	0.088	0.088	0.071	1.239	0.215	-0.051	0.229	R
1: O1,O2,O3,T1	0.061	0.061	0.049	1.245	0.213	-0.035	0.157	R
2: O1,O2,T1,O3	–0.110	–0.109	0.066	1.655	0.098	-0.240	0.020	R
1: AI1, IA2,IA3,T1	–0.029	–0.028	0.069	0.423	0.673	-0.166	0.106	R
2: IA1,IA2,T1,IA3	0.060	0.059	0.054	1.096	0.273	-0.047	0.166	R

The CTA carried out in the research shows that all the indicators have a reflective structure. The measurement model provides percentage correlations, with absolute values less than or equal to 0.1. In particular, the CI low adj (adjusted lower confidence interval) and CI up adj (adjusted upper confidence interval) values show opposite directions compared to the corresponding correlation loadings. The research considered PLSc (Consistent PLS) appropriate for evaluating the measurement model, as shown in Table 1. Procedural and statistical remedies were applied to mitigate the potential common method variance from a single data source. The researchers performed Harman's single-factor test to assess the presence of common method variance. The results indicated that a single factor accounted for only 35.4% of the total variance of 70%. In order to ensure that there was no multicollinearity between the variables, various checks were carried out, including examining tolerance values, variance inflation factor (VIF), and correlations between the variables. Following the guidelines of Hair et al. (2017), the bivariate correlations among the variables were less than 0.70, and the VIF values were less than 3.0. These results confirm the absence of multicollinearity.

Outer loadings, composite reliability (CR), and Average Variance Extracted (AVE) results were analyzed to examine convergent validity. It was found that there were no items with factor loadings below 0.50. The CR (rho_a and rho_c) values of all scales were greater than 0.60 (Bagozzi & Yi, 1988), and the AVE values were more significant than 0.50 (Fornell & Larcker, 1981). Cronbach's alpha was calculated to confirm the reliability of the scales. The reliability values of all scales are higher than 0.60 (see Table 2).

Upon examining the Fornell-Larcker criterion (Fornell & Larcker, 1981), it was found that the square root values of AVE were higher than the correlation loadings of the scales. This indicates that the scale exhibits convergent validity, surpassing the correlation loadings with other scales. Consequently, the analyses proceeded without modifications. Additionally, the cross-loading values of the scales were calculated to assess discriminant validity. It was observed that the correlation loadings between the indicators within each scale were higher than the loadings with indicators from other scales (Hair et al., 2022). Discriminant validity was further evaluated using the heterotrait-monotrait ratio (HTMT), Fornell-Larcker criterion, and cross-loadings. The HTMT scores exceeded the minimum criterion of 0.9 (Henseler et al., 2016), affirming discriminant validity (see Table 3).

Table 2 Reliability and Validity

Variables and Items	λ	a	rho_a	rho_c	AVE
Technology					
Robotic technologies provide a relative advantage to hotel businesses (increase market share, improve service, increase profitability).	0.887	0.940	0.942	0.941	0.762
Robotic technologies offer compatibility for hotel businesses. It is compatible with other technologies currently in use.	0.904				
Robotic technologies are more complex to use in hotels than other applications. It is challenging to integrate robotic applications into the existing business.	0.826				
Robotic technologies can be observed in hotel businesses. The use of robotic technologies makes it easier to monitor customer demands.	0.825				
Robotic technologies are controllable. It is easier to test.	0.917				
Environment					
The intensity of competition may increase with robotic technology.	0.944	0.953	0.953	0.953	0.872
The level of competition may change with robotic technology.	0.930				
The bandwagon effect may increase with robotic technology (the reason a hotel innovates is not its original idea but the tendency to innovate because other competitors are doing the same thing).	0.927				
Organization					
With robotic technology, management relationships, including the degree of centralization of the hotel, may become more prominent.	0.961	0.949	0.950	0.949	0.862
Robotic technology can enhance staff relations, including the degree of formalization of the hotel.	0.893				
Robotic technologies can provide organization in all departments of the hotel	0.929				
Intention to Adopt Robotic Technology					
If I decide on the hotel, I would like to adopt robot technologies in the future.	0.884	0.921	0.921	0.921	0.796
I predict that I would adopt robot technologies in the future if I were a decision-maker for the hotel.	0.906				
If I were a decision-maker for the hotel, I would try to adopt robot technologies in the future.	0.886				

Table 3 Fornell Larcker Criterion and HTMT Ration

	IART	O	E	T	IART	O	E	T
IART	**0.892**				-			
O	0.593	**0.928**			0.593	-		
E	0.613	0.518	**0.934**		0.612	0.517	-	
T	0.801	0.527	0.684	**0.873**	0.802	0.527	0.685	-

When assessing discriminant validity through cross-loading values, the factor loadings of the indicators on their assigned construct must be higher than the loadings on other constructs, assuming that the factor loadings are significant, typically above 0.70 (Hair et al., 2017). The analysis results found that the factor loadings of the indicators exceeded all loadings on other constructs, thus satisfying the final stage of discriminant validity (see Table 4).

Table 4 Cross Loadings Result

	IART	O	E	T
IART1	**0.884**	0.521	0.534	0.716
IART2	**0.906**	0.541	0.562	0.717
IART3	**0.886**	0.525	0.543	0.710
O1	0.570	**0.961**	0.508	0.515
O2	0.530	**0.893**	0.458	0.460
O3	0.551	**0.929**	0.475	0.490
E1	0.578	0.520	**0.944**	0.657
E2	0.570	0.465	**0.930**	0.615
E3	0.568	0.465	**0.927**	0.644
T1	0.710	0.476	0.624	**0.887**
T2	0.724	0.468	0.611	**0.904**
T3	0.661	0.443	0.519	**0.826**
T4	0.661	0.421	0.599	**0.825**
T5	0.734	0.488	0.628	**0.917**

Several indices were examined to assess the goodness of fit of the model. Firstly, the standardized root mean square residual (SRMR) was assessed and found below the recommended threshold of 0.080, indicating a satisfactory fit (Hu & Bentler, 1998). In addition, the normed fit index (NFI) was considered, which ranges from 0 to 1. The obtained NFI value of 0.930 indicates a relatively good fit as it approaches 1 (Bentler & Bonett, 1980).

The study also examined the d_ULS and d_G values, which represent the differences between the observed and predicted covariance matrices. Both the d_ULS and d_G values were found to be higher than the critical value of 0.05, indicating an acceptable fit (Dijkstra & Henseler, 2015). Additionally, the goodness of fit (GoF) value, which provides an overall assessment of the fit of the model, was evaluated. The obtained GoF value of 0.750 exceeded the recommended threshold of 0.36, indicating a good fit (Tenenhaus et al., 2005). These results show that the model has a favorable goodness of fit, as indicated by the SRMR, NFI, d_ULS, d_G and GoF values (see Table 5).

In addition, to ensure the absence of multicollinearity, the InnerVIF values of the scales were examined, all of which were less than 5. This indicates that there were no significant issues of multicollinearity among the variables. In addition, the strength of the relationship between the dependent and independent variables was evaluated. The study found that all dependent variables had robust explanatory power with a ratio greater than or equal to 0.50 (Henseler et al., 2009) (see Table 6). The study also examined the d_ULS and d_G values, which represent the differences between the observed and predicted covariance matrices. Both the d_ULS and d_G values were found to be higher than the critical value of 0.05, indicating an acceptable fit (Dijkstra & Henseler, 2015). Additionally, the goodness of fit (GoF) value, which provides an overall assessment of the fit of the model, was evaluated. The obtained GoF value of 0.750 exceeded the recommended threshold of 0.36, indicating a good fit (Tenenhaus et al., 2005). These results show that the model has a favorable goodness of fit, as indicated by the SRMR, NFI, d_ULS, d_G and GoF values (see Table 5).

Table 5 Model Goodness of Fit Result

	Saturated model	Estimated model	Critical Value	References
SRMR	0.024	0.024	0.08	Hu & Bentler, 1998
d_ULS	0.061	0.061	0.05	Henseler et al., 2016
d_G	0.232	0.232	0.05	
X^2	435.900	435.900	-	Dijkstra & Henseler, 2015
NFI	0.930	0.930	0.80	Bentler & Bonett, 1980
GoF	0.750	-	0.36	Tenenhaus et al., 2005

To assess the predictive capability of the research model, the RMSE (Root Mean Square Error) and MAE (Mean Absolute Error) results were compared using the Q^2predict index (Chin, 2010) and examined for symmetrical distribution (Sarstedt et al., 2022). The scale items' Q^2predict index values were positive and greater than 0, indicating good predictive performance (Sarstedt et al., 2018) (see Table 6).

The effect size in the structural model was assessed using f^2 analysis. According to Cohen's (1988) guidelines, effect sizes with coefficients of 0.02 and above are considered small, 0.15 and above are considered moderate, and 0.35 and above are considered significant. The results indicated that the effect sizes were generally moderate. To assess the predictive power of the model, the R^2 value was examined. R^2 is a coefficient that indicates the percentage of variance in the endogenous variables that are explained by the exogenous variables (Hair et al., 2022) (see Table 6).

Table 6 Inner Model Results

	InnerVIF	f^2	R^2	Q^2predict	RMSE	MAE
IART			0.683	0.596	0.639	0.447
O	1.480	0.108				
E	2.009	0.005				
T	2.035	0.643				

According to the path analysis results, technology ($\beta = 0.644$, $p < 0.05$) and organization ($\beta = 0.225$, $p < 0.05$) have a significant positive effect on the intention to adopt robotic technologies. Therefore, hypotheses H_1 and H_2 are accepted. Environment ($\beta = 0.055$, $p > 0.05$) does not significantly affect the intention to adopt robotic technologies. Accordingly, hypothesis H_3 is not accepted (See Table 7). Figure 1 shows the results of the research model.

Table 7 Structural Properties (Hypothesis Testing)

	HYPOTHESIS	β	X̄	S.d.	t	p	R
H_1	T → IART	0.644	0.643	0.065	9.872	0.000	√
H_2	O → IART	0.225	0.225	0.058	3.909	0.000	√
H_3	E → IART	0.055	0.057	0.059	0.944	0.345	X

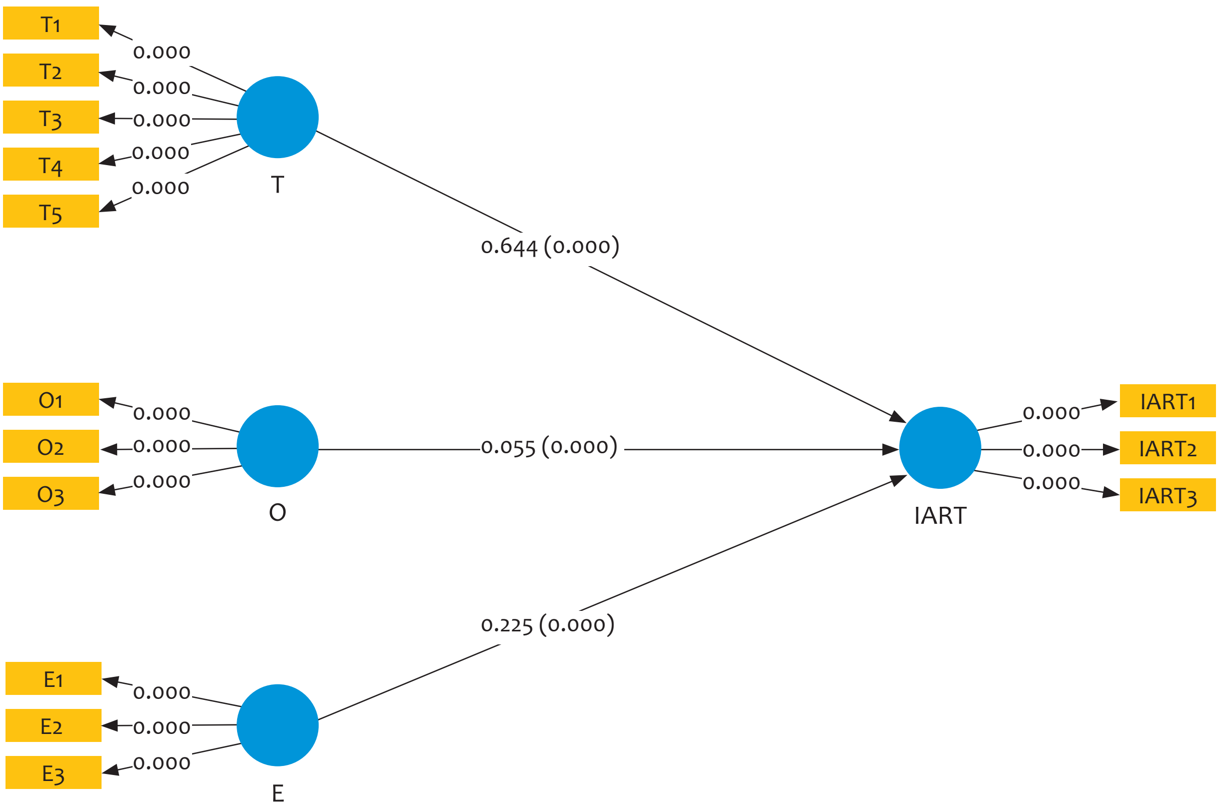

Figure 1 Research Model Results

The results of this study are consistent with several previous studies that have examined the adoption of robotic technologies in various industries (Baker, 2012; Fu et al., 2022; Ikumoro & Jawad, 2019; Oliveira & Martins, 2011; Miller, 2015; Pan et al., 2022; Pizam et al., 2022). Studies that focus on the technological factors influencing adoption consistently highlight the positive impact of technology readiness and compatibility on adoption intentions, consistent with our findings. Hotel managers who perceive robotic technologies as compatible with their existing systems and have a high level of technological readiness are more likely to adopt them (Ameen et al., 2021; Buhalis et al., 2020; de Kervenoael et al., 2020; Gretzel et al., 2015). This suggests that organizations should prioritize providing appropriate training and support to increase the technological readiness of their managers and employees.

Regarding organizational factors, our findings are consistent with previous research that emphasizes the importance of top management support and organizational resources in driving technology adoption. Hotel managers who perceive strong support from top management and have access to sufficient resources are likelier to adopt robotic technologies (Awa et al., 2017; Cabral & Jabbour, 2020; Lee et al., 2021). Organizations should therefore create a supportive and resourceful environment to encourage the adoption of robotics in the hospitality industry. However, it is essential to note that our study did not find a significant influence of environmental factors on adoption intentions. This finding contrasts with previous studies emphasizing the role of environmental factors, such as competitive pressures and regulatory requirements, in shaping technology adoption (Ameen et al., 2021; Buhalis et al., 2020). The lack of a significant effect may suggest that the hotel industry, at least in the context of this study, is less affected by external environmental factors when it comes to adopting robotic technologies. Further research could explore this aspect in more detail to comprehensively understand the contextual influences on adoption behavior.

NCA was used to test the necessary effects of technology organization and environment on adoption intention. We averaged the relevant items for each construct and performed permutation tests with 10,000 random resamples. We evaluated CE-FDH lines for the two relationships with satisfaction measured by a single item and CR-FDH lines for the remaining ones. The results revealed that environment (9,091%) has necessary effects on adoption intention, while technology and organisation do not have necessary effects on adoption intention. Furthermore, the bottleneck technique helps to identify the threshold conditions necessary to reach a certain level of outcome (see Table 8 and Figure 2).

Table 8 NCA Result

	Effect size	Obs. above ceiling	Accuracy	Slope	Intercept	Condition I.	Outcome I.	Rel. I.	Abs. I.	NCA	%
T	0.000	0.000	100.000	n/a	n/a	n/a	n/a	n/a	n/a	40%	0.000
O	0.000	0.000	100.000	n/a	n/a	n/a	n/a	n/a	n/a	40%	0.000
E	0.007	1.000	99.747	1.967	5.158	91.860	82.917	98.609	10.136	40%	9.091

In the research model, we used an importance-performance matrix analysis (IPMA) to examine its relationship with the dependent variable, adoption intention. IPMA is a comprehensive grid-based analysis that combines the critical effects of the IPMA PLS-SEM estimation with the average performance score (Hock et al., 2010). This analytical approach allows for a detailed assessment of the relative importance and performance of different factors in influencing adoption intentions. By analyzing the significant effects, we can understand how each factor influences the dependent variable. At the same time, the average performance score allows us to assess how well each factor achieves the desired outcome. Using IPMA, researchers can understand how importance and performance interact to identify critical factors that significantly influence adoption intentions. This analysis provides valuable information that can be used to make decisions and develop effective strategies to increase the adoption of a particular concept, product, or behavior (see Figure 3).

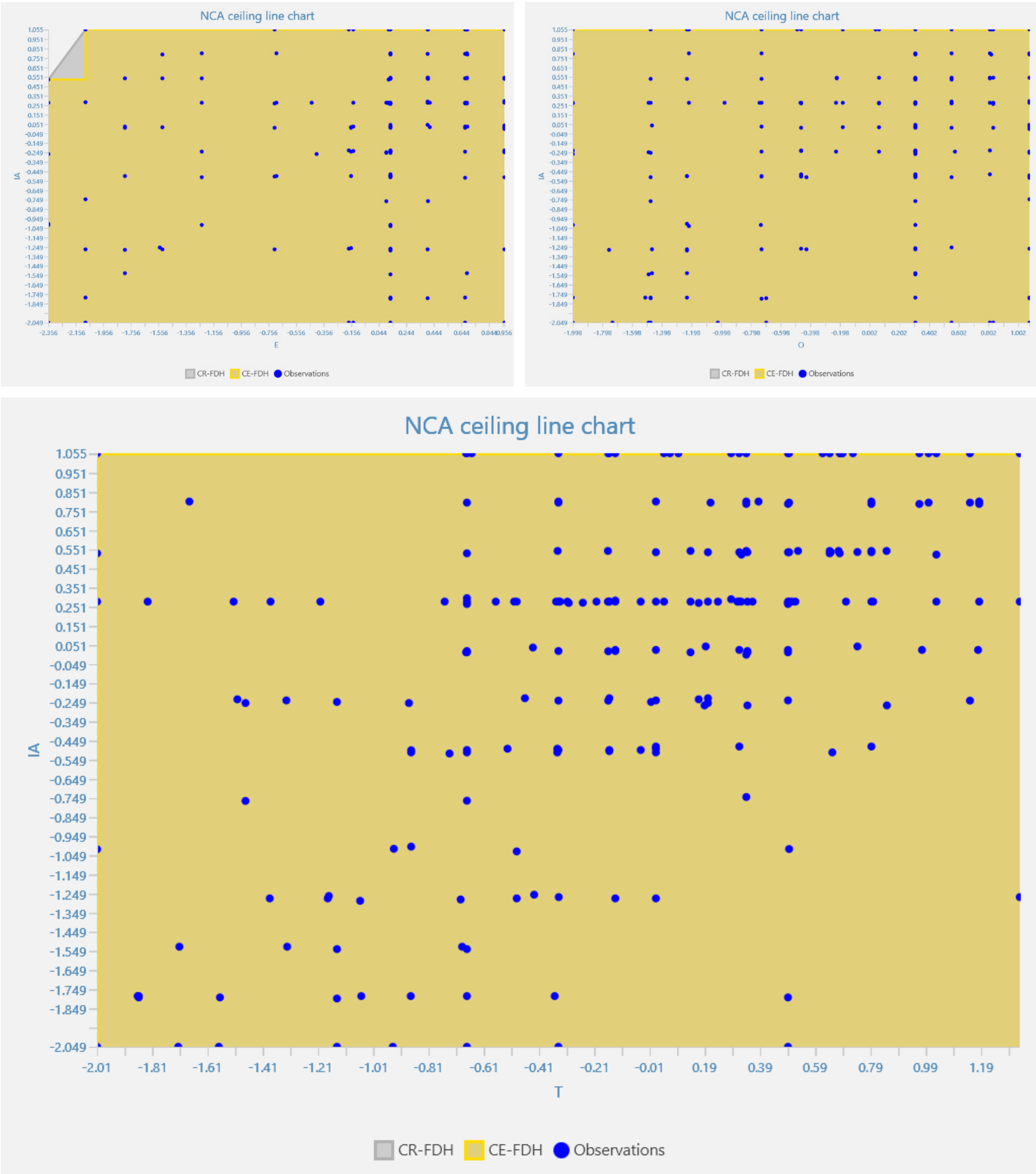

Figure 2 Environment NCA Ceiling Line Chart

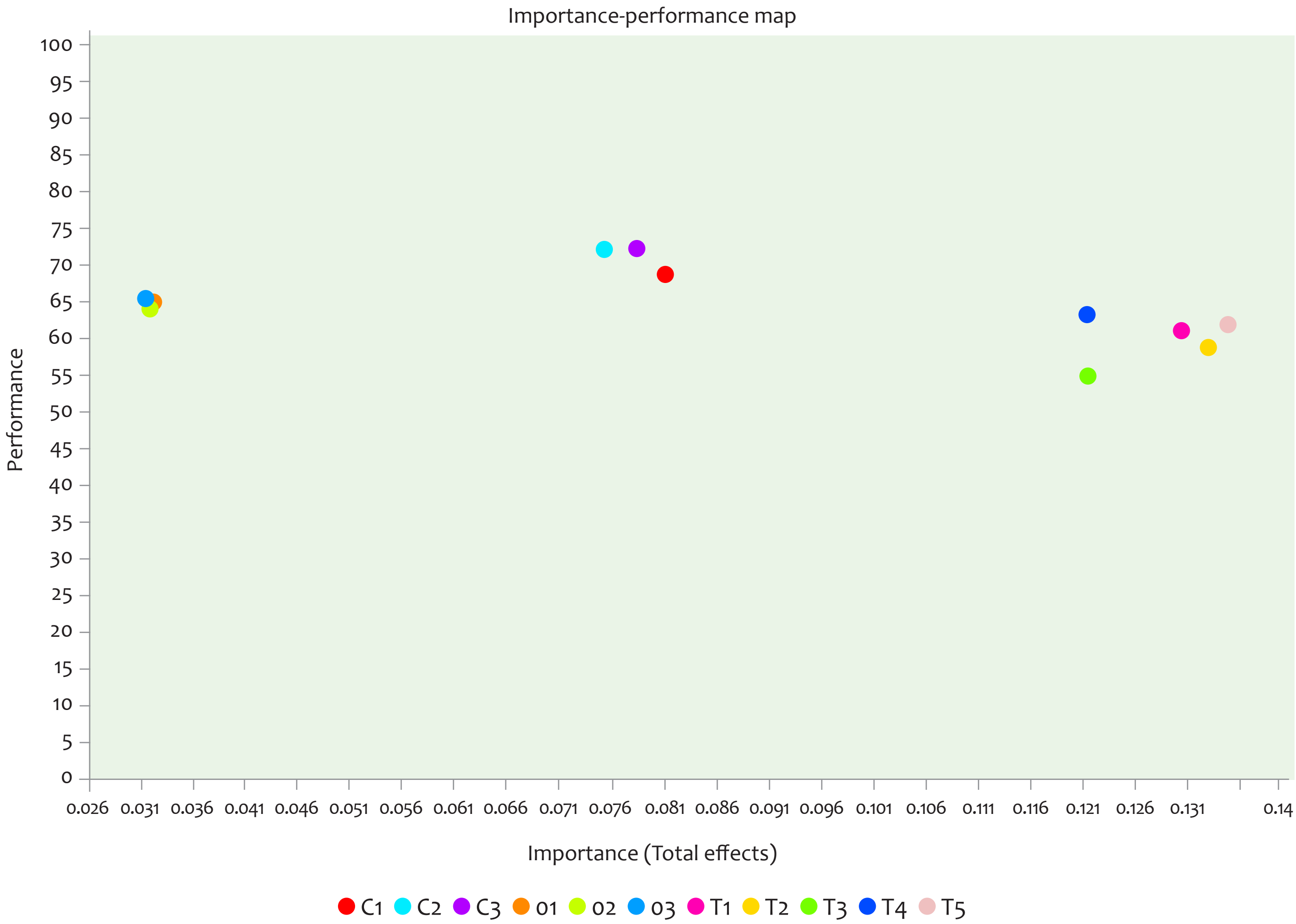

Figure 3 IPMA Result

CONCLUSION

This paper extensively investigates the attitudes of hotel managers towards the implementation of robots and robotic technologies using the TOE framework. The study focuses on understanding how technological, organizational, and environmental factors influence hotel managers' intentions to adopt robotic technologies in the accommodation and tourism sector. The research results clearly show that both technological and organizational factors have a significant and positive impact on the intention to adopt robotic technologies, thus confirming hypotheses H_1 and H_2. However, it was observed that the environment does not play a significant role in influencing adoption intentions, leading to the non-confirmation of hypothesis H_3.

The adoption of robotic technologies in hotels is relevant to sustainability. It can help hotels become more environmentally friendly and socially responsible while improving operational efficiency and guest experiences. Robotic technologies can make hotel operations more efficient by automating cleaning and room service tasks. This reduces resource consumption and waste, which is good for the environment. It also frees up hotel staff to focus on providing better services to guests. By integrating sustainability features into robots, hotels can offer eco-friendly experiences to their guests. For example, robots can suggest environmentally friendly activities or help guests conserve energy in their rooms. This appeals to the growing number of environmentally conscious travelers and helps hotels stand out. Robots can also contribute to social responsibility by assisting guests with special needs and disabilities. They can provide inclusive services and improve accessibility within the hotel. Additionally, robots can reduce physical strain on hotel staff, creating a safer and healthier work environment. However, it is essential to consider sustainability throughout the entire lifecycle of robotic technologies. This means considering their environmental impact during production, use, and disposal. It also means ensuring fair employment practices and protecting the privacy of guest data.

This research study makes a valuable and significant contribution to the existing literature concerning the integration of robotic technologies in the hospitality industry, offering important theoretical implications. By applying the TOE framework (Technological, Organizational, and Environmental), the research enhances our understanding of the factors that influence the intention to adopt robots in this sector. The findings emphasize the crucial role of technological and organizational factors in driving adoption intentions while shedding light on the limited impact of the external environment. This nuanced perspective enhances our theoretical understanding of technology adoption by emphasizing internal organizational factors and the contextual influence of the external environment.

Furthermore, this study extends the application of the TOE framework to the hotel industry, providing valuable insights into how hotels perceive and evaluate disruptive technologies such as robots. Utilizing an established theoretical framework, the research strengthens our understanding of the adoption process and highlights the interplay between technological, organizational, and environmental factors. For future studies in the service sector examining the adoption of new technologies, considering these factors could prove highly beneficial.

From a practical standpoint, the study results hold significant implications for decision-makers and practitioners in the hospitality industry. Identifying the technological and organizational factors influencing the intention to adopt robots can help managers make informed decisions about integrating and implementing robots in their hotels. The study highlights various potential benefits of robots in the industry, including improved service speed and accuracy, reduced staff workload, and cost savings.

Additionally, the research underscores the importance of considering contextual factors and the external environment when implementing robotic technologies. While this study did not find significant impacts from external factors, being aware of these influences can aid decision-makers in assessing the feasibility and sustainability of robot implementation in different hotel contexts. Understanding the external environment, including market conditions, industry trends, and regulatory frameworks, can help managers make informed decisions and align their adoption strategies with the broader industry landscape. Moreover, the study highlights how robotic technologies can support sustainability efforts in the tourism sector, especially during exceptional situations like pandemics. Utilizing robots for cleaning, disinfecting, and maintaining hygiene can enhance guest safety and satisfaction.

However, it is essential to acknowledge some limitations in the study. It solely focused on the perspectives and intentions of hotel managers, and future research should include other stakeholders, such as hotel staff, guests, and technology providers, to gain a more comprehensive understanding of the adoption process and potential challenges from different viewpoints. Furthermore, conducting research in different regions or countries would increase the external validity of the findings.

The study's cross-sectional design provided a snapshot of adoption intentions at one point in time, but a longitudinal study design could provide deeper insights into the dynamics and changes in adoption intentions and behaviors over time. Additionally, future research could incorporate qualitative methods, such as interviews or focus groups, to gain more profound and nuanced insights into the factors influencing robotic technology adoption. While this study examined intentions to adopt robotic technologies, it did not explore actual adoption and its outcomes. Therefore, future research could investigate the implementation and outcomes of robotic technology adoption in the hospitality industry, including factors that influence successful implementation, organizational implications, and guest experiences.

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