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EMBRACING INTELLIGENT HOSPITALITY: EXPLORING ROMANIAN CONSUMERS' ACCEPTANCE OF AI AND ROBOTIC TECHNOLOGIES

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Abstract

This paper examines the role of robots in the hospitality industry through their large-scale implementation, highlighting several relevant issues. The integration of advanced technologies has become a key pillar of the hospitality industry, particularly in the tourism sector. In recent years, ongoing digitalization has led to significant transformations in the tourism ecosystem. Today, the hospitality industry serves as a dynamic testing ground and implementation site for smart technologies, especially service robots. The need to increase efficiency, personalization, and service flexibility according to tourists' preferences has encouraged the adoption of intelligent technologies, whose acceptance varies depending on the cultural characteristics of each country. To explore the acceptance of robots and the intention to use them in hotels, this study integrates key theoretical and methodological elements, focusing on the Technology Acceptance Model (TAM). Data were collected from a sample of 109 individuals in October 2025, and the hypotheses were tested using SmartPLS software. The model employed in this study shows that understanding and acceptance are influenced by perceived ease of use, perceived usefulness, and self-efficacy, each mediated by individuals' attitudes toward adopting robots. This study contributes to understanding how to integrate robots and smart technologies within the hospitality industry, providing insights into strategies for integrating robots based on respondents' opinions.

Keywords: robots, artificial intelligence, hospitality industry, Technology Acceptance Model (TAM), technology

JEL Classification: F21, L86, O31, O33, Z32

1. Introduction

This paper analyzes the impact of large-scale robot implementation in the hospitality industry, focusing on how customers perceive and adapt to emerging technologies. The 21st century, marked by rapid technological advancement and continuous innovation, has significantly influenced tourists' expectations and behaviors. As a result, hospitality companies must adapt to these evolving trends to maintain trust, market presence, and brand reputation (Gutierriz et al., 2025). In this context, the integration of robotics may represent a significant opportunity for innovation within the sector. The relevance of this study stems from ongoing global developments and strategic considerations related to the adoption of robotic technologies.

The primary aim of this paper is to examine how young Romanian people perceive the growing role of service robots in the hospitality industry and their impact on performance. This work reviews relevant theoretical frameworks, technological developments, regulations, and key limitations related to the classification and implementation of service robots in this sector. However, a comprehensive analysis was limited by the respondents' restricted direct interaction with robots. In today's market, collecting feedback and understanding the social and economic benefits of robotic technologies are essential aspects of hospitality research.

This research is driven by the increasing interest in integrating robotics within the hospitality sector. Robots represent a crystallization of artificial intelligence, differing from traditional technologies through the combination of AI capabilities, consumer expectations, and service orientation (Savela et al., 2018). As tourism continues to expand, the characteristics of robots are becoming increasingly relevant for the hotel industry. The study is based on the premise that adopting innovative technologies represents a competitive advantage (Gomezelj, 2016). This paper explores Romanian citizens' attitudes and perceptions toward adopting new technologies, highlighting perceived usefulness in the hospitality industry, ease of use in environments such as hotels and restaurants, and the role of individual attitudes in shaping interactions with smart technologies.

The adoption of robots has attracted growing academic attention. Research has shown that factors such as perceived usefulness, perceived attributes, and the degree of human-likeness influence customer acceptance. However, most existing studies focus on developed markets, with limited attention to the Eastern European context. Against this backdrop, this paper examines key dimensions of technology acceptance, with particular emphasis on its main determinants and influencing factors.

The current context underscores the importance of examining user acceptance, which, according to Dahlin (2019), is a key determinant of service success. Davis et al. (1989) define acceptance as a combination of attitudes, intentions, and behavior. The research employs the TAM model to investigate the use of robots in hospitality, as it is a well-established framework in the literature. The main objectives of the study are to explore citizens' opinions toward the acceptance of robots, to develop and empirically validate the acceptance construct through testing methods, and to examine the relationships between perceived usefulness, ease of use, attitude, and self-efficacy.

The following section presents a literature review of smart technologies and their implications for society and the hospitality industry. The subsequent sections focus on the research methodology and empirical results. The paper concludes with final remarks, including conclusions and recommendations on how the findings can be applied in practice.

2. Analysis of the literature on conceptual dimension and evolution of robot technology

2.1 Conceptual dimension and evolution of robot technology

In the complex global environment marked by uncertainty, restructuring, and continuous change, technology has become a fundamental pillar of the hospitality industry. Increasing tourist demand and rising customer expectations have prompted hotel managers to adapt their operational strategies to enhance competitiveness. The shift toward technology involves implementing smart-driven solutions to ensure efficiency and long-term performance. The current context, with the integration of artificial intelligence and robotics, has shaped organizational policies toward constant innovation based on international trends. Their significance was already highlighted in earlier research, where technological progress was seen as a force capable of fundamentally transforming industries and redefining traditional development patterns (Collier, 1983; Drexler & Lapré, 2019).

The history of the robot dates to the 1920s, when Czech writer Karel Capek introduced the term "robot" in his work Rossum's Universal Robots. Later, Isaac Asimov contributed by popularizing these technologies in his science fiction works. The robotics revolution accelerated in 1961 with the creation of Unimate, the first industrial robot (Ivanov & Webster, 2019). Thus, robots have become important factors in competition and differentiation within the industry.

In the context of continuous change, ensuring efficiency in the hospitality industry has become a key priority, driving the adoption of artificial intelligence and, subsequently, robotics. Initially, companies focused on digitalization by creating chatbots and service-oriented platforms. Later, they integrated operating systems and AI-based technologies, as noted by Mariani et al. (2018). As a result, they concentrated on smart tools such as Siri, Amazon Alexa, and Google Assistant.

The adoption of robots has been particularly significant in several Asian countries, which are recognized for their advanced technological infrastructure. These technologies operate at different levels of artificial intelligence, ranging from mechanical systems designed for standardized tasks to more advanced applications capable of simulating elements of human-like intuition and contextual analysis. Recent industry reports highlight rapid development, while previous research suggests that the technology-driven workforce may expand significantly by 2030, potentially reaching a growth rate of up to 25% (Bowen & Morosan, 2018; Palrão et al., 2023). Overall, these trends emphasize the growing importance of technology in the hospitality industry and reflect a shift toward a more innovation-oriented organizational approach.Increasing robot automation and customer interaction has led hotels to adopt service robots to meet new industry demands. They are defined by Park (2020, p.5) as 'smart tools that can feel, think and act to improve/extend human productivity. Chiang and Trimi (2020) further described service robots as 'front-to-face agents that interact directly with customers, making the technology a direct player'.

Based on their classification, service robots can be grouped into quai-automated and fully automated systems (Park, 2020). Moreover, Chiang and Trimi (2020) identify professional robots designed to perform dangerous tasks and automated activities. Reiser et al. (2013) extended their classification by including personal service robots that support customers. However, service robots still face limitations in the range of activities they can perform. Ivanov, Dolgui, and Sokolov (2022) believe that robots are used for washing, providing information, processing payments, bartending, and food service. In the same note, Palrão et al. (2023) thinks that they can assist customers by offering menu information and delivering room service.

2.2 Technological progress and emerging application in the hospitality industry

Rapid advances in AI and robotization have significantly increased interest in their application within the field of tourism and hospitality (Liu et al., 2024, p. 2). The Cambridge Dictionary (2025) defined robotization as 'the act or process or integrating robots (computer-controlled machines) to accomplish the work done by people in the past'. Given this definition, it can be stated that the automation trend becomes a certain pattern.

Recent studies indicate that the development of autonomous robots in the hospitality sector has evolved, being influenced by both external and internal factors (Grobbelaar & Verma, 2024). According to Kim et al. (2021, p. 3), 'service robots are currently used in a wide range of hospitality services', from check-in and check-out processes to cooking and cleaning. Hotels benefit from the implementation of service robots through increased productivity, reduced costs and increasing competitiveness. For guests, these technologies contribute to shorter waiting times and more a unique and enjoyable experience.

COVID-19 pandemic: Kim et al. (2021, pp. 3-4) argue that customer preferences have shifted due to external pressures and global events. As a result, many customers now prioritize health and safety over human interaction. In response, the hospitality industry has adopted technology-based solutions to minimize physical contact and maintain hygiene standards.

Labor shortages: Ivanov (2024, pp. 566–568) suggests that RAISA technologies can help address labor shortages in hospitality and tourism. He identifies three main approaches: replacement (substitution), such as digitizing concierge services through chatbots; improvement (augmentation), by increasing employee productivity and assigning robots to specific tasks; and transformation, by introducing services such as robot-assisted room service and integrating digital responsibilities into job roles. Regarding the future application of robots in the hospitality industry, Yang, Henthorne and Babu (2020, pp. 221-224), argue that robotic 'technology has already penetrated various departments of the hospitality industry', while future directions indicate a broader expansion:

Hotels: the following perspectives are to broaden the directions of application in areas such as laundry services, voice and mobile ordering systems within hotel rooms. Consequently, a greater degree of automation in hotels is expected. Restaurants: restaurants can achieve a high level of automation with robotic cashiers, robot waiters, robot chefs, which will allow them to compete with large restaurant chains. Meetings and events: supporting telepresence by using robots or virtual reality (VR) to be present in place of humans at meetings (e.g.: MantaroBot).

However, the future role of robots and artificial intelligence in the hospitality industry remains uncertain, as replacing human interaction with robotic services may diminish the core of hospitality (Shukla et al., 2024). Hospitality is defined as the ability of service providers to make guests feel welcomed and appreciated (Kim et al., 2020). Hospitality relies heavily on emotional engagement, which is difficult to replicate through technological means and remains largely dependent on human staff (Golubovskaya et al., 2017).

Although prior studies have examined the acceptance of technology and artificial intelligence in hospitality, most have focused on Asian markets, particularly China, South Korea, Taiwan, and Japan. For example, Zhong et al. (2020) found that usefulness, attitude, and value shape Chinese consumers' acceptance of smart technologies. Similarly, Tuomi et al. (2021) explored the theoretical and managerial implications of service robots in hotels in the United States and Japan, highlighting the growing role of automation.

Regional differences matter in hospitality robotics because culture, technological familiarity, and digitalization shape consumer acceptance. Studies in Asian countries, where automation is more advanced, report more positive attitudes toward robotic services and AI in hospitality (Zhong et al., 2020; Kim et al., 2021). In contrast, European studies highlight concern about authenticity, emotional interaction, trust, and the loss of human contact (Nam et al., 2021; Park, 2020; Savela et al., 2018).

Even though research on service robots has grown, studies on Eastern Europe, particularly Romania, remain limited. Most evidence comes from technologically advanced markets, with far less attention to lower-digitalization settings where exposure to robotic services is limited (WIPO, 2025). As a result, it is unclear whether findings from Asian contexts apply to Eastern European consumers. This study aims to address this gap in the literature by examining Romanian consumers' acceptance of service robots in the hospitality industry through the perspective of the Technology Acceptance Model (TAM).

3. Research on the perception of Romanians regarding the adoption of new technologies in the hotel industry

3.1 The importance of the acceptance of user model

The hospitality industry relies heavily on a human workforce, so adopting robots in a sector where emotional aspects and human characteristics are important is crucial for adapting accommodation services to new realities. Previous studies have highlighted the need to use these technologies in hotel operations, finance, marketing, and human resources, as well as the long-term benefits for companies seeking to differentiate themselves in a competitive market (Ivanov et al., 2020).

Although the literature highlights several advantages, most research has focused primarily on Asia. European studies on service robots are almost nonexistent, making Eastern Europe a region of interest for studying tourists' perceptions and technology acceptance. Moreover, previous studies have concentrated on countries with a high level of technological development (Nam et al., 2021), so this paper examines the importance of studying contexts where technologies are still in an early or experimental stage.

Romania represents a particularly relevant case, as it is an EU member state but remains less digitally developed compared to many of its European counterparts. According to the Global Innovation Index (GII), which considers innovative capabilities and the percentage of the global economy, Romania ranks 49th out of 139, last among EU member states, with a score of 34.3 (WIPO, 2025). The Romanian state and its approach to adopting these technologies become a fundamental topic of analysis.

The Technology Acceptance Model was developed in the early 1980s, beginning with Rogers' (1983) innovation diffusion theory. In 1985, Davis introduced TAM, which is based on rational behavior theory and assumes that individuals are rational and that human social behavior is not affected by unconscious incentives or forces. Davis et al. (1989) further developed the Technology Acceptance Model and demonstrated that perceived usefulness and ease of use influence consumers' perceptions and attitudes. Similarly, Kulviwat et al. (2007, p. 1066) noted that consumer decision-making and actual behavior are influenced by new technologies.

3.2 Development of hypotheses and the research model

The Technology Acceptance Model (TAM) explains how individuals form intentions to adopt and use new technologies through key cognitive and attitudinal determinants. Among the most influential constructs of TAM are perceived usefulness (US) and perceived ease of use (EU), which have been widely applied in studies examining technology acceptance in hospitality and service environments (Davis et al., 1989).

Perceived usefulness (US) refers to the extent to which individuals believe that using technology can improve their performance or overall experience (Davis et al., 1989; Nysveen, 2005). Previous research demonstrated that perceived usefulness significantly influences consumers' willingness to adopt innovative technologies and smart services (Nysveen, 2005; Petschnig et al., 2014). In hospitality settings, service robots may enhance efficiency, convenience, and customer experience, which can contribute to more favorable evaluations of such technologies (Begum et al., 2025).

Perceived ease of use (EU) reflects the degree to which individuals believe that interacting with technology requires little effort (Davis et al., 1989; Or et al., 2011). Technologies perceived as intuitive and user-friendly are more likely to generate positive evaluations and acceptance among consumers (Or et al., 2011). Prior studies also highlighted that perceived usefulness (US) and perceived ease of use (EU) equally represent central determinants of technology acceptance, as they influence how individuals evaluate and respond to innovative systems (Or et al., 2011; Petschnig et al., 2014).

Attitude represents an individual's positive or negative evaluation regarding the use of a technology and is considered a 'prominent construct' (Begum et al., 2025, p. 9) of technology acceptance theory (Begum et al., 2025). In the context of hospitality service robots, favorable attitudes may emerge when consumers perceive robotic services as useful, accessible, and capable of improving their experience. Based on the literature, the following hypotheses are proposed; Hypothesis 1 (H1), that states how perceived usefulness (US) positively influences consumers' attitude (AT) toward using service robots in hospitality. And hypothesis 2 (H2), that states how perceived ease of use (EU) positively influences consumers' attitude (AT) toward using service robots in hospitality.

In addition to the traditional TAM constructs, this study includes self-efficacy (SE) as a predictor of attitudes toward service robots. Self-efficacy refers to individuals' confidence in their ability to use technology effectively in specific situations (Bandura, 1997; Giger et al., 2025). In hospitality settings, consumers who feel capable of interacting with robotic technologies may experience less uncertainty and greater confidence. Previous research suggests that self-efficacy supports technology acceptance by shaping users' attitudes, behavioral responses, and willingness to engage with smart technologies (Alghamdi et al., 2024; Lim et al., 2011). Therefore, the following hypothesis is proposed*;* Hypothesis 3 (H3)*, stating how s*elf-efficacy (SE) positively influences consumers' attitude (AT) toward using service robots in hospitality.

Attitude has consistently been identified as a strong predictor of behavioral intention within technology acceptance research. Wang et al. (2016) demonstrated that favorable attitudes toward smart technologies significantly increase individuals' intention to adopt and use them. Similarly, studies in hospitality contexts showed that consumers with positive perceptions of service robots are more likely to express willingness to interact with robotic services in hotels, especially when robots work in front-office (Choi et al., 2020; Fuentes-Moraleda et al., 2020). Accordingly, the following hypothesis is proposed*;* Hypothesis 4 (H4)*, that talks about how* consumers' attitude (AT) positively influences behavioral intention (BI) to use service robots in hospitality.

This study examined the relationship between attitude, perceived usefulness, perceived ease of use, self-efficacy, and behavioral intention to use service robots in the hospitality industry. Zhong et al. (2020) stated that perceived usefulness and perceived ease of use significantly predict consumers' attitudes, which in turn influence behavioral intention. The authors highlighted that self-efficacy plays a crucial role in reducing the perceived complexity of service robots, thereby increasing users' acceptance of smart technologies.

In this study, attitude is conceptualized as a mediating variable connecting perceived usefulness, perceived ease of use, and self-efficacy with behavioral intention to use service robots in hospitality settings. Based on this reasoning, the following mediation hypotheses are proposed: H5a. Attitude (AT) mediates the relationship between perceived usefulness (US) and behavioral intention (BI); H5b. Attitude (AT) mediates the relationship between perceived ease of use (EU) and behavioral intention

(BI); and H5c. Attitude (AT) mediates the relationship between self-efficacy (SE) and behavioral intention (BI). Thus, Figure 1 proposes the following research model:

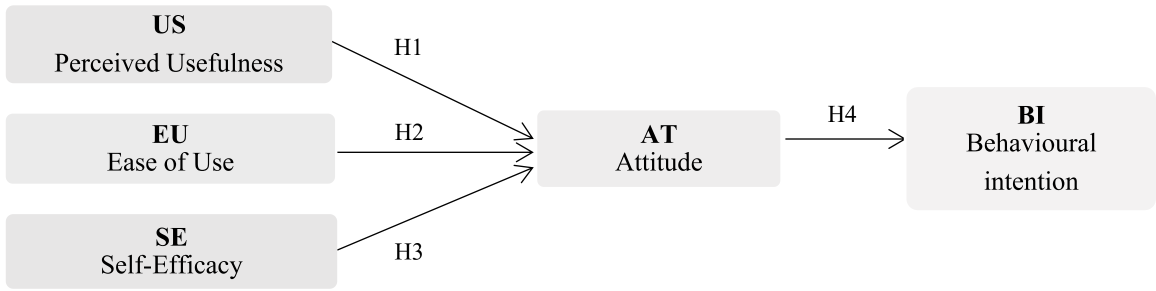

Figure 1. Proposed research model
Source: Developed by the author

4. Methodology

4.1 Data collection

A thorough review of the literature was conducted to identify the main factors and variables influencing the use of robots in hotels, including ethics, tourists' desire to use technology, intention to return, perceived anthropomorphism, attitude, and sentimental value (Lim et al., 2011; Nysveen, 2005; Or et al., 2011; Wang et al., 2016; Zhong et al., 2020). This research focuses on Romania, where, as previously noted, the level of innovation remains relatively low compared to other European Union countries, as indicated by the Global Innovation Index (WIPO, 2025). This situation underscores the need to investigate technology adoption in a context where advanced technologies are not yet widely integrated, to better understand the conditions and potential drivers of development, while also providing valuable insights for businesses seeking to implement service robots.

Following guidance from the literature (Lim et al., 2025), this study used an online survey method with a combination of purposive and snowball sampling techniques. Purposive sampling involved recruiting participants familiar with emerging technologies such as artificial intelligence and other software, while snowball sampling was used to recruit additional participants who met the criteria. Data were collected through an online survey platform, specifically Google Forms. The research targeted students studying tourism or those who had already completed a bachelor's or master's degree.

The study included 109 respondents, with data collected between October 22, 2025, and November 15, 2025. Questionnaire items were measured using a five-point Likert scale ranging from '1' = strong disagreement, '2' = disagreement, '3' = neutral, '4' = agreement, and '5' = total agreement (Table 1). This scale is widely used to assess attitudes, perceptions, and opinions by converting subjective responses into statistical data (Koo & Yang, 2025). The motivation for this choice is its ability to provide sufficient detail while remaining easy for respondents to understand and use. The study variables – perceived ease of use (EU), perceived usefulness (US), behavioral intention (BI), attitude (AT), and self-efficacy (SE)—were adapted from Zhong et al. (2020).

Table 1. Variables and items

Latent variable	Item	Reference
Perceived usefulness	I believe that hotel robots can help me save time during my visit.	US1
	The services provided by hotel robots are more efficient than traditional ones.	US2
	I believe that using robots makes the hotel experience more comfortable.	US3
	Overall, I believe that robots can meet needs during my stay.	US4
Perceived ease of use	I expect the interaction with a hotel robot to be simple and intuitive.	EU1
	I believe I can quickly learn how to use a robot in a hotel, without additional help.	EU2

Latent variable	Item	Reference
	I believe I could communicate with a robot as I would with a real person in a hotel.	EU3
Self-efficacy	I believe I can quickly learn how hotel robots' work.	SE1
	I am confident in my abilities to use a hotel robot correctly.	SE2
	I believe hotel robots are easy to use and intuitive.	SE3
	I would not need much training to use a robot in a hotel.	SE4
Attitude	I have a favorable opinion about the use of robots in hotels.	AT1
	I believe that robots can improve customer experience in hotels.	AT2
	I find the idea of interacting with robots interesting and positive.	AT3
Behavioral intention	I plan to choose a hotel that uses robots in the future.	BI1
	I would recommend my friends to try a hotel that uses robots.	BI2
	I plan to stay at a hotel with robot services.	BI3
	If I have the opportunity, I will prefer a hotel with robot services.	BI4

Source: Adapted from Zhong et al. (2020)

The sample size of 109 respondents exceeded the minimum requirement according to the "10-times rule," which states that the minimum sample size should be at least ten times the maximum number of structural paths directed toward any endogenous construct in the model (Barclay et al., 1995). In the proposed model, attitude (AT) is the construct with the highest number of incoming structural paths, specifically from perceived usefulness (US), perceived ease of use (EU), and self-efficacy (SE). Therefore, the minimum required sample size is 30 respondents. Thus, the sample is considered adequate for the analysis (Lim, 2025).

Although the 10-times rule is a simplified guideline, it is frequently used in exploratory PLS-SEM studies. Consequently, the sample size is considered sufficient for the present analysis. These responses are sufficient for conducting Partial Least Squares Structural Equation Modeling (PLS-SEM) according to Hair et al. (2025) and Sarstedt et al. (2021). For this study, the statistical method was performed in two parts: the measurement model and the structural model, involving the testing of the latent structural model (Anderson & Gerbing, 1988).

4.2 Respondent profile and measurement model

Table 2 provides a demographic summary of the participants, including gender, age, educational background, socio-professional status, and average monthly income, as these aspects are relevant to the study's purpose. Most respondents identified as male (57.8%), while women comprised 42.2%. The largest group was aged 18–28 years (98.2%), followed by those aged 29–44 years (1.8%). In terms of education, more than half of the respondents held a bachelor's degree or were undergraduate students (71.6%), 25.7% held a master's degree, and 2.8% had completed high school. Regarding socio-professional status, most respondents were students (82.6%), while 17.4% were employed. Most participants reported a monthly income between 2,000 and 3,500 lei (62.4%), followed by 3,501–5,000 lei (27.5%), 5,001–6,500 lei (2.8%), and over 6,500 lei (3.7%). Those without income accounted for 1.8%, as did those with income below 2,000 lei.

This study used Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 4.0 to analyze the data set (Pham & Duong, 2024). Assessment of the measurement model involved evaluating the reliability and validity of the variables used to measure the theoretical constructs (Gao et al., 2024). SmartPLS was considered appropriate for this research because it accommodates complex theoretical models involving various types of latent variables, making it suitable for exploratory research and for testing theoretical models. Additional reasons for selecting this method include its ability to manage predictive models, enhance understanding of endogenous constructs, provide efficiency in parameter estimation, and examine interrelationships (Hair & Sabol, 2025; Sarstedt et al., 2021).

Table 2. Profile of participants

Variable	Group	Frequency	Percent (%)
Gender	Female	46	42.2%
	Male	63	57.8%
Age	18-28 years	107	98.2%
	29-44 years	2	1.8%
	45-60 years	0	0%
	61+ years	0	0%
Education	High school	3	2.8%
	Undergraduate Bachelor's degree	78	71.6%
	Master's degree	28	25.7%
	Postgraduate doctoral degree	0	0%
	No studies	0	0%
Socio professional status	Student	90	82.6%
	Employee	19	17.4%
	Entrepreneur	0	0%
	Unemployed	0	0%
	No profession	0	0%
Monthly income	Under 2000 lei	2	1.8%
	Between 2000-3500 lei	68	62.4%
	Between 3501-5000 lei	30	27.5%
	Between 5001-6500 lei	3	2.8%
	Across 6500 lei	4	3.7%
	No income	2	1.8%

Source: Authors' elaboration based on Google Forms data

5. Data analysis and results

5.1 Measurement model

The measurement model was evaluated by examining internal consistency reliability, convergent validity, and discriminant validity. Internal consistency was evaluated using Cronbach's alpha (CA) and composite reliability (CR), while convergent validity was assessed through the average variance extracted (AVE). Discriminant validity was examined using the Heterotrait–Monotrait ratio (HTMT) and the Fornell–Larcker criterion.

The results in Table 3 indicate satisfactory reliability and convergent validity for all constructs. Cronbach's alpha values range from 0.706 to 0.902, exceeding the recommended threshold of 0.70 proposed by Nunnally (1978). Similarly, composite reliability values are above the recommended threshold of 0.70 suggested by Hair and Sabol (2025) and Sarstedt et al. (2021), confirming acceptable internal consistency reliability. Additionally, all AVE values exceed the recommended threshold of 0.50 (Hair et al., 2019), supporting convergent validity.

Table 3. Factor loadings, reliability and validity

	Cronbach's alpha	CR (rho_a)	AVE
AT	0.885	0.889	0.813
BI	0.902	0.905	0.772
EU	0.706	0.706	0.630
SE	0.875	0.878	0.728
US	0.891	0.893	0.753

Source: Authors' calculations using SmartPLS.

Discriminant validity was further examined through confirmatory factor analysis, following Lim (2025). The constructs demonstrated acceptable validity, with all AVE values exceeding the 0.50 threshold recommended by Hair and Sabol (2025) and Hair et al. (2019). Discriminant validity was also assessed using the HTMT criterion, with most values remaining below the 0.85 threshold proposed by Henseler et al. (2015). The results are presented in Table 4.

Table 4. Discriminant validity using HTMT

	AT	BI	EU	SE	US
AT					
BI	0.753				
EU	0.904	0.726			
SE	0.796	0.580	0.927		
US	0.808	0.646	0.917	0.760	

Source: Authors' calculations using SmartPLS.

The HTMT results indicate that most construct pairs are within acceptable limits. However, three construct pairs slightly exceed the conservative threshold of 0.85 and exceed 0.90- EU-AT, SE-EU- and US-EU. Therefore, bootstrapped confidence intervals were additionally examined. The results show that the confidence intervals for these construct pairs include the value of 1, indicating that discriminant validity between these constructs may not be fully established. As a result, some conceptual overlap between perceived ease of use, perceived usefulness, and self-efficacy cannot be entirely ruled out.

To further assess discriminant validity, the Fornell–Larcker criterion was applied by comparing the square root of AVE values with inter-construct correlations. The results are presented in Table 5.

Table 5. Fornell–Larcker criterion

	AT	BI	EU	SE	US
AT	**0.901**				
BI	0.679	**0.878**			
EU	0.717	0.583	**0.794**		
SE	0.703	0.520	0.727	**0.853**	
US	0.725	0.587	0.730	0.672	**0.868**

Source: Authors' calculations using SmartPLS.

The Fornell–Larcker results indicate that the square root of AVE for each construct is generally higher than the correlations with other constructs, indicating acceptable discriminant validity. Although several HTMT values suggest possible conceptual overlap between certain constructs, the overall measurement model demonstrates acceptable reliability and validity.

Overall, the results indicate that the constructs used in this study meet the recommended thresholds for internal consistency and convergent validity. However, the HTMT findings suggest that some constructs, particularly perceived ease of use (EU), perceived usefulness (US), and self-efficacy (SE), may share conceptual similarities. Therefore, the measurement model can still be considered adequate for the purposes of the present exploratory analysis.

5.2 The structural model

After confirming the reliability and validity of the measurement model, the structural model was evaluated using Partial Least Squares Structural Equation Modeling (PLS-SEM) in SmartPLS 4.0. The evaluation of the structural model was conducted by examining path coefficients (β), t-values, and p-values obtained through the bootstrapping procedure. Bootstrapping is considered an appropriate method in PLS-SEM because it allows the statistical significance of the hypothesized relationships to be tested without assuming data normality (Hair et al., 2019; Sarstedt et al., 2021). Therefore, the structural model results are presented in Figure 2 and Table 6.

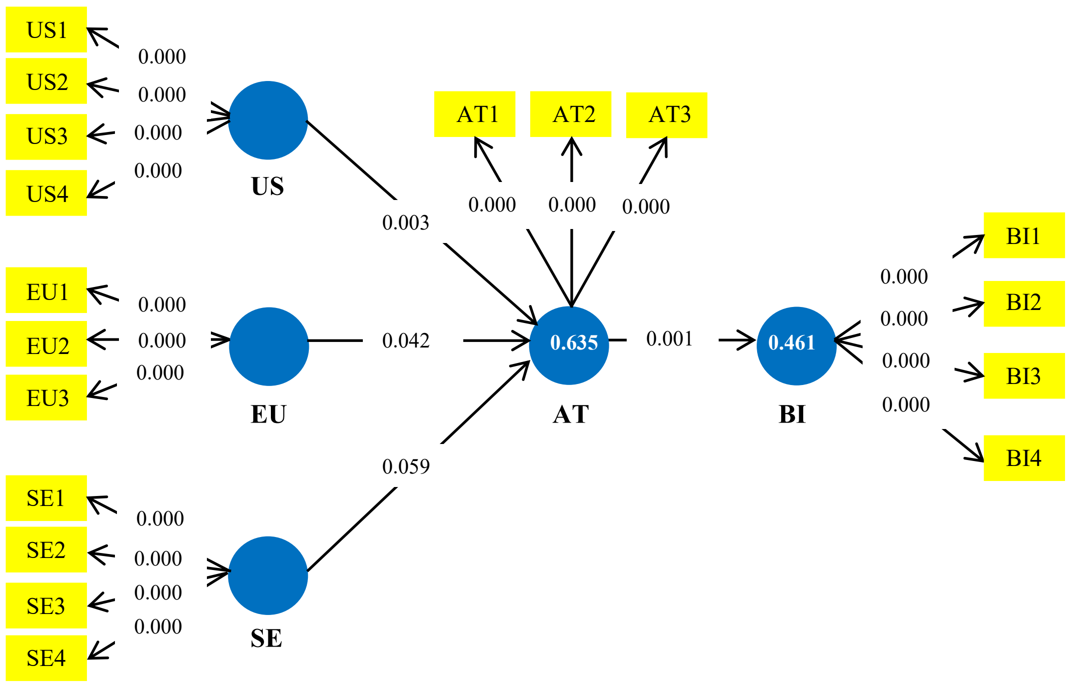

Figure 2. Results of proposed research model

Source: Developed by author

The results indicate that perceived usefulness (US) has a positive and statistically significant effect on attitude (AT) ($\beta = 0.345$, $t = 2.937$, $p = 0.003$), supporting H1. Similarly, perceived ease of use (EU) positively influences attitude (AT) ($\beta = 0.261$, $t = 2.032$, $p = 0.042$), supporting H2. The effect of self-efficacy (SE) on attitude (AT) is positive but does not reach the conventional 0.05 significance threshold ($\beta = 0.281$, $t = 1.888$, $p = 0.059$). Therefore, H3 is not supported at the 5% significance level, although the result may be considered marginal. Finally, attitude (AT) has a strong and statistically significant effect on behavioral intention (BI) ($\beta = 0.679$, $t = 9.501$, $p = 0.001$), supporting H4.

Table 6. Hypothesis testing

Hypotheses	Path	β	Stand. Dev.	t-value	p-values	Decision
H1	US->AT	0.345	0.118	2.937	0.003	Supported
H2	EU->AT	0.261	0.128	2.032	0.042	Supported
H3	SE->AT	0.281	0.149	1.888	0.059	Not supported
H4	AT-> BI	0.679	0.071	9.501	0.001	Supported

Source: Authors' calculations using SmartPLS.

5.3 Mediation analysis

To examine the mediating role of attitude (AT), specific indirect effects were assessed using bootstrapping procedures in SmartPLS. Since the proposed structural model does not include direct paths from perceived usefulness (US), perceived ease of use (EU), and self-efficacy (SE) to behavioral intention (BI). Regarding Table 7, the analysis focuses exclusively on the significance of indirect effects through attitude (AT).

Table 7. Mediation analysis

Hypothesis	Path	Indirect Effects			Decision
		β	t-value	p-value	
H5a	**US->AT->BI**	0.234	2.731	0.006	Supported
H5b	**EU->AT->BI**	0.177	1.907	0.057	Not supported
H5c	**SE->AT->BI**	0.191	1.944	0.052	Not supported

Source: Authors' calculations using SmartPLS.

The results indicate that the indirect effect of perceived usefulness (US) on behavioral intention (BI) through attitude is positive and statistically significant (β = 0.234, t = 2.731, p = 0.006). Therefore, H5a is supported. This finding suggests that consumers who perceive service robots as useful are more likely to develop favorable attitudes, which subsequently increase their intention to use robotic services in hospitality settings.

The indirect effect of perceived ease of use (EU) on behavioral intention through attitude is positive but does not reach the conventional significance threshold of 0.05 (β = 0.177, t = 1.907, p = 0.057). Therefore, H5b is not supported, although the result may be interpreted as marginally significant. Similarly, the indirect effect of self-efficacy (SE) on behavioral intention through attitude is positive but not statistically significant at the 0.05 level (β = 0.191, t = 1.944, p = 0.052). Therefore, H5c is not supported at the conventional significance threshold, although the relationship appears close to significance.

6. Discussion

The findings of this study confirm the central role of attitude in explaining consumers' behavioral intention to use service robots in hospitality settings. Consistent with the Technology Acceptance Model (TAM), perceived usefulness and perceived ease of use significantly influence consumers' attitudes toward robotic services. These findings are aligned with previous research conducted in hospitality and technology acceptance contexts, which emphasized that consumers are more likely to adopt innovative technologies when they perceive them as useful, efficient, and easy to interact with (Davis et al., 1989; Wang et al., 2016; Zhong et al., 2020).

Among the constructs examined, perceived usefulness shows the strongest indirect effect on behavioral intention through attitude. This finding suggests that practical value and functional efficiency are key drivers of technology acceptance in hospitality settings. Similar results were reported by Choi et al. (2020) and Fuentes-Moraleda et al. (2020), who found that consumers evaluate service robots more positively when they enhance service efficiency and customer experience. In emerging digital contexts, perceived usefulness may therefore influence adoption more strongly than technological familiarity.

The results also indicate that perceived ease of use positively influences attitude toward service robots. This finding supports previous TAM-based studies arguing that technologies perceived as intuitive and user-friendly are more likely to generate favorable consumer evaluations (Kulviwat et al., 2007; Or et al., 2011). In hospitality settings, ease of interaction may reduce consumers' uncertainty and increase their openness toward robotic services.

In contrast, self-efficacy does not significantly affect attitude at the conventional 0.05 level. Although the relationship is positive, consumers' confidence in using robotic technologies alone may not be enough to generate favorable attitudes toward service robots. This finding relatively differs from previous studies that identified self-efficacy as an important driver of technology acceptance and behavioral responses (Alghamdi et al., 2024; Giger et al., 2025). One possible explanation is that Romanian consumers have limited direct exposure to robotic services in hospitality settings, which may reduce the role of self-efficacy in shaping attitudes.

The mediation analysis further indicates that attitude mediates only the relationship between perceived usefulness and behavioral intention. Although perceived ease of use and self-efficacy show positive indirect relationships with behavioral intention, these effects remain only marginally significant. This finding reinforces the importance of perceived usefulness as the main psychological mechanism through which consumers develop intentions to adopt service robots in hospitality settings.

Overall, the findings support the argument that technology acceptance is context-dependent (Nam et al., 2021; Savela et al., 2018). In lower digitalization environments such as Romania, consumers may rely more strongly on perceptions of usefulness and practical benefits than on technological confidence alone. The study therefore extends existing hospitality robotics literature by providing empirical evidence from an underexplored Eastern European context characterized by lower levels of technological integration and consumer exposure to robotic services.

Conclusions, limitations and future work

This study examined the acceptance of service robots in the hospitality industry by applying the Technology Acceptance Model (TAM) in the Romanian context. The research investigated the relationships between perceived usefulness (US), perceived ease of use (EU), self-efficacy (SE), attitude (AT), and behavioral intention (BI) toward using service robots in hospitality settings.

The findings indicate that perceived usefulness and perceived ease of use positively and significantly influence consumers' attitudes toward service robots. In addition, attitude was found to have a strong positive effect on behavioral intention, confirming its central role within the technology acceptance process. In contrast, self-efficacy did not significantly influence attitude at the conventional 0.05 significance level, suggesting that consumers' confidence in their ability to use robotic technologies may not necessarily translate into favorable evaluations of service robots.

The mediation analysis further revealed that attitude significantly mediates only the relationship between perceived usefulness and behavioral intention. This finding highlights the importance of functional value and practical benefits in shaping consumers' intentions to adopt robotic services in hospitality environments.

From a theoretical perspective, the study contributes to the existing hospitality robotics and technology acceptance literature by extending TAM within a lower digitalization environment. The findings support the argument that technology acceptance is context-dependent (Nam et al., 2021; Savela et al., 2018), as consumers in emerging technological contexts may rely more strongly on perceptions of usefulness and usability than on technological confidence alone.

From a managerial perspective, the results suggest that hospitality organizations should prioritize the implementation of service robots that provide clear functional benefits and user-friendly interactions. Demonstrations, guided interactions, and gradual integration strategies may help consumers develop more favorable attitudes toward robotic services. At the same time, hospitality managers should maintain an appropriate balance between automation and human interaction, as consumers may still value human contact in service environments (Chiang & Trimi, 2020; Ivanov et al., 2020).

Several limitations should be acknowledged. First, the sample is highly homogeneous, as 98.2% of respondents were aged between 18 and 28 years and 82.6% were students. The predominance of younger respondents may partially reflect the online distribution strategy of the questionnaire, which relied mainly on university-related groups and social media platforms frequently used by younger individuals. Consequently, the findings cannot be generalized to the broader Romanian population and should be interpreted primarily in relation to younger consumers with higher exposure to digital technologies.

Second, the study was based on self-reported perceptions rather than direct interactions with service robots. As a result, respondents' evaluations may reflect expectations or imagined experiences instead of actual behavioral responses in real hospitality settings.

Third, the study's cross-sectional design limits its ability to assess causal relationships or changes in technology acceptance over time. Consumers' perceptions of service robots may shift as exposure to these technologies increases in the hospitality industry.

Finally, several HTMT values exceeded the recommended thresholds, and their bootstrapped confidence intervals included 1, indicating possible conceptual overlap among perceived usefulness, perceived ease of use, and self-efficacy. Although the measurement model showed acceptable reliability and convergent validity, future research should refine the measurement scales and test the model with larger, more diverse samples.

Future research should consider more diverse demographic samples and include participants with direct experience interacting with service robots in hospitality settings. Longitudinal studies may provide additional insights into how familiarity and repeated interaction influence technology acceptance over time. Furthermore, future studies could extend the proposed model by incorporating additional variables such as trust, perceived risk, anthropomorphism, privacy concerns, or emotional attachment toward robotic technologies.

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Abbreviations: The following abbreviations are used in this manuscript: Artificial intelligence (AI), attitude (AT), average variance extracted (AVE), behavioral intentions (BI), Cronbach's alpha (CA), composite reliability (CR), perceived ease of use (EU), Global Innovation Index (GII), human–computer interaction (HCI), heterotrait–monotrait ratio of correlations (HTMT), partial least squares structural equation modeling (PLS-SEM), robotics, artificial intelligence and service automation (RAISA), self-efficacy (SE), Technology Acceptance Model (TAM), perceived usefulness (US), and virtual reality (VR).

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