

Article

The Effect of Perceptions on Service Robot Usage Intention: A Survey Study in the Service Sector

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Abstract: The current age of artificial intelligence, along with the advent of robots, portends increased use of innovative technologies in the tourism industry, with higher levels of service innovation than in many other industries. In addition, factors such as an approaching worldwide pandemic have limited the amount of physical contact that people can have. So as a result, the use of service robots in service areas, such as tourism, has recently become controversial. In this study, accommodation customers' perceptions of advantages and disadvantages about robots and the effect of the perceived value of their intention to use them were investigated. Within the scope of the research, data were collected from 1408 people living in various cities in Turkey through an online survey. The data were analyzed by structural equation modeling. As a result of the analyses, it was found that the perception of advantage and the perceived value affect the intention to use service robots positively and significantly. It has been determined that the perception of disadvantage affects the intention to use service robots negatively and significantly. The research results show that the accommodation companies should be innovative and rapidly transition to robotization, as in the manufacturing industry. Advanced technological innovation applications, such as service robots, will play an essential role in the revival of the tourism industry, especially during the global epidemic.

Keywords: service robots; innovation; artificial intelligence; tourism; hospitality; sustainability



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1. Introduction

As the world has become increasingly technological, it is almost hard to overlook its changes to the way people live. An increasing number of technology breakthroughs, such as artificial intelligence, cloud computing, and blockchain, are rapidly and continually changing society and the marketplace [1]. As a result of the change, the pressure prompted increased market competitiveness, which drove companies to hunt for innovative solutions to address it. Companies have a strong propensity to be innovative and try various new approaches to getting their employees innovating. Studying the advances businesses have made on the concept of innovation has made it a discipline, and this has brought forth several theories on it. Innovation can disrupt the established way of doing things [2] because each invention offers a way to displace the conventional techniques [3]. Nevertheless, it is stressed in the literature that innovation provides companies a competitive advantage by helping them in developing new products and processes [4].

Artificial intelligence and robots present an enormous opportunity for travel, tourism, and hospitality companies to enhance their operations and productivity and consistently deliver high-quality products and services to their clients [5]. In this way, they are changing how tourism works [6]. These potentials have increased the importance of robotics in the hospitality and tourism industries. This significance became apparent following the

COVID-19 outbreak, which not only demonstrates the existing employment of robots in everyday tasks but also reveals the possibility for robots to be used in a variety of other fields, including distribution, entertainment, cleaning, guidance, and security [7]. Especially after the epidemic, the hospitality industry can use robots in different scenarios that can help reduce infection, such as preparing food, creating “safe” distanced spaces [8], disinfection, monitoring, distribution [9].

Artificial intelligence-based systems not only trigger service and process automation but are also used for direct interaction with customers in various pre-service [10]. Increasingly integrated with tourism and hospitality services, AI and robotics are valuable for explaining the relationships between trust and the premises and consequences of trust, improving the knowledge base on human–robot interactions in tourism service environments [11]. Robots can differentiate from competitors, achieve and sustain competitive advantage, and improve quality in the service sector. Hospitality companies depend on robots to provide superior services, such as cooking and serving food and beverages, welcoming guests, transporting products [12]. These robots are typically used in hospitality and tourism to assist customers or tourists with routine tasks, such as finding their way around a hotel, securing or unlocking hotel room doors, providing food or beverages, and offering other cleaning and security services [13].

With all those mentioned above, the fact that technological developments are already changing existing business models, regardless of the pandemic, also ensures that robots are seen as a factor that can reduce costs in the hospitality industry [12]. Currently, the aim is to bring together employees and technology in hotel operations at an optimum level. Hotel companies want to improve process efficiency by connecting their processes with intelligent technologies, facilitating human–technology interaction. While the pandemic will eventually pass, the hospitality business will not revert to its “pre-pandemic” state. Customers will demand better standards of hygiene and safety and will retain their social distance. Embracing technology advancements during the pandemic [14] will become the standard in the future, as the WHO recommends using contactless services to combat COVID-19. However, rapid adaptation of hotel managers to robot technologies is essential to overcome their grievances during global epidemics and similar crisis periods, such as COVID-19. One of the sectors most affected by such crises is the tourism sector. The impact of the tourism sector causes income loss not only for hotels but also for countries. Seventy-five million jobs in the tourism sector are predicted to be at risk, and the business will lose \$2.1 trillion [15]. In particular, considering that millions of people were affected by COVID-19 [16], with borders closed, international travel restricted [17], and the work environment evolving, business demands [18] and customer behavior [19] are changing. It is unthinkable for the tourism industry to continue unaffected by such crises.

For this reason, governments should support these technologies and implement incentive programs to develop such technologies in the tourism sector. Innovation as a critical risk-reduction strategy is likely to play an essential role in the hotel industry’s recovery from such crises [20]. Robots are one of the most significant technological innovations to date [21]. Robots can navigate complex service environments thanks to advanced image recognition and processing techniques and have complex interactions with humans due to their increased natural language processing capabilities [22] and thus advanced robots with artificial intelligence equipped with machine learning applications are used in hotels, airports, and restaurants [23]. Crises, such as COVID-19, create a unique situation for hospitality companies, requiring them to place a greater emphasis on customer and employee health and safety and the physical distance that robots can successfully give [12]. Thus, the pandemic has made this application unprecedentedly relevant to the hospitality industry as we look to a possible near future with more robotic applications to reduce human contact [24]. It also increased the importance that accommodation companies attribute to technology, especially robots, for less human contact and more automation [25].

For the reasons listed above, service robots in the hospitality industry have become a crucial issue. At this point, the question that arises for hotel companies, whether the

investment required for the use of service robots is cost-effective. In order to answer this question, several issues need to be examined. First, how will the relationship between robots and their customers be formed, and will customers accept these robots? Second, are these robots sustainable in terms of technological infrastructure? Third, is the company that will invest in service robots ready for this innovation in its business model and management approach? Undoubtedly, each of these questions continues to be discussed separately in the literature, and the scientific gap on the subject is tried to be filled. This study focuses on the first of these questions and aims to measure the perceptions and attitudes of hotel customers towards service robots. In this context, the research questions were formed as follows:

RQ1: In the service industry, to what extent do customers think that the use of service robots is advantageous or disadvantageous affects their intention to use this service?

RQ2: In the service industry, does the perceived value of service robots by customers encourage them to use them?

To address these questions, we conceptualize a structural equation model that aims to measure the influences of perceived advantages, disadvantages, and value on intention to use to understand hotel customers' current situation. This research will give us a clearer understanding of the effects of customer perceptions on their intention to use service robots.

The content of this article is organized as follows. Section 2 of the study summarizes the relevant literature on service robots in the tourism industry regarding service robots and customer acceptance and the formulation of hypotheses of the study. Section 3 discusses the sample selection process, survey, data collection stages, and analysis methods used in the study. Section 4 presents the analysis findings in tables and figures. Section 5 discusses the findings, considering the relevant literature. Finally, Section 6 summarizes the results and limitations of the study and provides some suggestions for future research.

2. Literature Review and Hypothesis Development

2.1. Service Robots

The industry 4.0 revolution has made many vital changes. One of the most critical of these changes was the implementation of robot technology. Robotic technology is beginning to be widely used in industrial organizations, and it has proven especially helpful in production environments [26]. Although the robot technology that comes with industry 4.0 is perceived as a disruptive technology [27], the appeal of this technological innovation is much more robust in service industries (such as health, transportation, etc.), which are considered labor-intensive industries [28]. Therefore, robots in service industries can be characterized as a revolution in technological innovation [29].

The term "robot" comes from the Czech word "robota", which translates as "forced labor". While the concept was formerly used to mean stupid machines that perform trivial, repetitive tasks, it has evolved to describe intelligent anthropomorphic robots in popular culture [28]. Robots are characterized as "reprogrammable multifunctional" devices that are programmed to move materials, parts, tools, or specialized equipment to execute a variety of activities [30]. Robots can perform a commonly complex set of actions. They can make autonomous decisions and have rapid adaptation to their environment, depending on data collected from multiple sensors and other sources, such as the perceive–think–act paradigm [29].

A service robot is a technology capable of doing physical activities, operating independently without human intervention, and being managed by computers without operator interaction [31]. Additionally, a service robot is characterized as an autonomous and adaptive interface that performs practical tasks for humans or equipment, interacts with them, and communicates with them [29]. A service robot is a robot that can interact with and engage people in a social environment [32]. They represent the addressee with whom a customer interacts in front-line service and can thus be seen as social beings.

What is significant in social interaction is that the robot is frequently a social entity that is partially automated throughout the service encounter; this refers to giving consumers the impression that they are interacting with another social entity [29].

Service robots can provide value-added services while complying with safety standards in human–robot interactions. Although functional tasks performed by service robots can also be achieved through other technologies (such as kiosks, mobile payments, and touch screens), service robots can provide front-line services where interaction is essential for customer experiences [33]. Service robots can change their sound patterns and speed to appear relevant and capable. For instance, finishing shades with a low pitch creates the illusion that service robots can assist customers in resolving their problems. While speaking, service robots face customers directly to communicate their interests. When they interact with clients, they use body language and facial expressions to aid incomprehension. For instance, when greeting customers from a distance, robots send a “Yes, I understand you” message accompanied by a slight nod or smile [34].

There is not yet a fully automated robot for the service sector. Most robotic solutions still require human control, and some autonomous solutions are limited to simplified functions [8]. Robots with social functions will soon become popular in human society. Despite significant technological advances in recent years, robots’ capacity to interact intuitively and socially with humans is still very limited [35].

The service robot deployment model proposes that service robots perform nearly any cognitively complex task and almost all low-emotional/low-social-complexity tasks. While service robots are incapable of deep emotional engagement, front-line workers will be responsible for emotionally and socially tricky service jobs [28]. As long as service robots fulfill the functional, social-emotional, and relational needs that encourage group cohesion, they will be well accepted by consumers [29].

A Softbank Robotics-developed robot, called Pepper, is the first commercially available robot with emotional intelligence. An autonomous robot endowed with the ability to read body language, facial expressions, and tone of voice helps to enable personalization in a market where customization is a growing necessity [36]. One example is when people felt upset, so it made them feel better. In addition, it might be able to recognize individuals by their voices and faces. It included sensors for gaming and social interactions that were operated with hand gestures. Companies in Europe, Asia, and North America use Pepper. For example, France’s national railroad, the Société Nationale des Chemins de Fer, used the social networking tool Pepper to deliver information about trains and their surroundings and entertain customers waiting. They also recorded customers’ levels of satisfaction with the services at these locations. Asia-based Pizza Hut uses the Pepper smart appliance to greet customers, take orders, and process orders. While on the Costa Cruise Lines’ service, passengers can enjoy the assistance of Pepper, which is available in three languages, English, German, and Italian. The most well-known asset at the Mandarin Oriental Hotel in Las Vegas, Nevada, is a technologist who is frequently seen serving guests with answers to hotel-specific details, guiding them, telling stories, and snapping selfies [34].

2.2. Service Robots in Hospitality

Service automation and robotic technologies have affected different areas of hotel operations. Hotels have implemented self-service kiosks that eliminate the need for front office personnel, letting customers complete check-in and check-out procedures without assistance. Over time, check-in/out services have been made available from mobile devices to further convenience and speed [37]. Robots meant to perform various tasks, such as delivering food and other things, checking in and out, and providing security and information, are increasingly being employed in the hospitality and tourism industries [7].

Service robots are categorized as semi-automatic or wholly automated, depending on their level of automation. Semi-automatic robots can do so with programming or human input via remote controls. On the contrary, automated robots are conscious agents capable

of reacting to changes in their environment and exchanging information without external control [38].

In anticipation of service robots providing reliable, convenient, and efficient service, several top hotels have lately adopted service robots to create distinctive guest experiences. For example, the Henn-na Hotel in Japan, which debuted in 2015 and was named the world's first robot-powered hotel by Guinness World Records, employs dinosaur- and anthropomorphic-shaped robots to carry up human staff duties [39]. Since then, this pioneering robot has expanded its operations into new geographies. The hotel employs dinosaur receptionists, robot movers, robot cloakrooms, and in-room personal robot assistants. While a fully robotic hotel remains a rarity today, hotels worldwide use intelligent automation for several customer-facing processes, including self-check-in, virtual personal assistants, and room delivery robots [31].

In much the same way, the Hotel Icon in Hong Kong has conducted trials with two different types of robots. They provide a service delivery robot and a cleaning robot developed by Konia Minolta [39]. A robotic butler distributes poolside towels and snacks at the Aloft Cupertino in California. Additionally, this robot is capable of delivering ordered things to guests through elevators. Botlr, Aloft's first robotic servant, is trained to bring "towels" and "small nibbles" to guests' rooms in response to their requests for snacks or toiletries [6]. Recently, robots began working in restaurants as chefs. For instance, CaliBurger has developed Flippy, a robot that cooks hamburgers in Pasadena, California. Additionally, students at the Massachusetts Institute of Technology and famous chef Daniel Boulud founded the Spyce restaurant in Boston, where food is cooked entirely by robots in an automated kitchen. It is widely regarded as the first restaurant to feature a robotic kitchen capable of cooking intricate dishes [40]. Savioké's Relay is employed in various hotels and primarily conducts delivery jobs in coordination with humans. Relay's cameras and sensors enable it to discern room numbers, navigate busy corridors, and take elevators without clashing with anything. When the Relay reaches its location, its lid automatically opens to let visitors receive their orders, including food and supplies. Guests are requested to submit feedback for Relay on a screen so that it is easier to ensure quality. Relay shakes his body in response to a favorable response from the guest system. This instance serves as a good representation of technological advancement and human-robot collaboration in hotels. Service robots must identify user emotions via bodily movements, facial expressions, and speech to respond compassionately during the contact to collaborate effectively with people. Advanced service robots must behave consistently with human personnel, displaying natural facial expressions and emotional responses [39].

Technology can change the way people see, perceive, and demand new technologies by affecting people's lives and perceptions. For instance, robots serve as information providers for guests in the hotel industry but may require interaction [41]. However, the community may oppose using service robots to deliver human services. In the literature, studies are indicating that the resistance to consumer service robots is vital, even if service robots in the tourist and hotel industry increase [42]. Reasons for this may include the lack of human contact with robots and ethical concerns about possible increased unemployment. Service robots replacing human personnel can pose a psychological challenge to the traditional view of service [33]. For instance, the anxiety induced by a robot may discourage humans from interacting with it [35]. In tourism and hospitality environments that rely heavily on human interaction, replacing human workers with robots alters the nature of the service experience by incorporating human-robot interactions and the potential to alter customer attitudes and behaviors [11]. In addition, technology anxiety expresses the concerns and fears of consumers about using new technology. In this context, technology anxiety is recognized as an essential psychological precursor affecting the adoption of new technology [10]. In other words, a customer's willingness to adopt new technology hinges on their confidence in how valuable that technology will be [29].

Individuals' acceptance and adoption of new technologies have been examined using the Technology Acceptance Model (TAM). TAM is used to measure the level of resistance

people must use new technologies, identify why people accept new technologies, predict how users will respond to new and emerging technologies, and examine how and how quickly the system and its practices are evolving [43]. The theoretical foundation of the model is based on Fishbein and Ajzen's Theory of Reasoned Action, which was first proposed in 1975. A related issue is that abstract concepts, such as beliefs and values, have weakened the Theory of Reasonable Action. As a result, TAM was refined over time. The model has become the most popular theory on the use of information technology and the best way to gauge people's intentions when it comes to using it [44]. More than a quarter of a century ago, Fred Davis first proposed TAM, and it has since become the standard model for research that investigates the influence of various variables on the adoption of new technology [45]. TAM is a significant model used to predict and explain customers' adoption of further information and communication technologies. The model indicates users' acceptance of technology by how useful, easy to use, and desirable it appears [46]. Based on the theory, the perception of ease of use and usefulness regarding information technology impacts how individuals use the technology [47]. Researchers have developed the TAM over time. Following those years, a modified version of the original TAM was created and known as the TAM 2. The acceptance of new technology is predicted by how much it benefits the individual and how useful and straightforward it is. The new model was successfully tested, and the results confirmed its suitability [48].

TAM intends to help businesses predict how their customers will respond to their various types of innovative technology. Davis et al. (1989) [49] conducted a study and found that ease of use and usefulness were two critical reasons influencing individuals' choice of information technologies. Some extrinsic variables affect individuals, organizations, and technology regarding usefulness and ease of use in the study. People's propensity to perform better in their work by using technology is known as perceived usefulness; Similarly, perceived ease of use refers to people's initial interest and ability to quickly pick up and use a particular technology without much effort [49]. The model's attitude, which results from emotions and ideas that accumulate, conveys the individual's emotional or cognitive response to the system. People's attitudes toward using information system applications can be described as evaluating their willingness to use the system [50].

The TAM has an essential explanatory power in identifying the reasons for end-users to accept new technologies. Making the best use of new technology is influenced by an individual's characteristics, expectations, and perceptions [51].

At this point, it is necessary to emphasize the advantages and disadvantages that customers think they will gain from preferring robots instead of humans. The advantages perceived by customers represent competitive benefits that they can get from robot services but not from human services. If customers think that an innovative service type is more advantageous than a traditional one, they prefer it [52]. Researchers discovered that customers in hotels and other lodging establishments accept and even enjoy robots due to their functionality, efficiency, and ease of use [53]. It is stated in the study done by Tavitiyaman et al. (2020) [54] that customers' perceptions of robot technologies greatly influence their preferences for hotels.

There are numerous positive examples of robots assisting their human counterparts. However, not everyone views robots positively. The more negative people's attitudes toward robots are, the less likely they are to use them [35]. Attitude is described as the acquired disposition of an individual's favorable or unfavorable attitude toward service robots, influencing the individual's thoughts and behavior. Attitudes are formed as a result of intricate psychological processes and serve as precursors to behavioral responses. They are critical factors in the adoption of robots [55].

As a result of their study, Christou et al. (2020) [41] found that people who were excited about new technology and advances in technology were concerned that robots could replace humans, and they could lead to social deterioration. Moreover, even people who are unconvinced about how technology shapes and influences society have admitted that robots are essential. While most respondents agreed, respondents felt that the most

effective way to pull customers in was by giving robots human-like features and design and including human-like emotions, personality, and voice in their approach. The participants believe that a robot in a hospitality or tourism environment should be a humanoid rather than any other type of machine.

Therefore, the following hypotheses have been formed:

Hypothesis 1 (H1). *The perceived advantage of service robots positively affects the intention to use them.*

Hypothesis 2 (H2). *The perceived disadvantage of service robots negatively affects the intention to use them.*

The evaluation of the relative rewards offered to the customer and the sacrifices he makes in return determines the perceived value [56]. Perceived value is typically the result of a trade-off between what customers receive and what they are willing to give up in exchange for it [57]. Perceived value is defined as an overall assessment of a customer's perceived benefits and sacrifices, as seen from the utility perspective. In other words, customers can cognitively integrate the things they purchase to purchase goods with their perceptions of these items [58].

It is possible that companies providing good service will not be enough to attract new customers or keep existing customers engaged because customers seek value in the form of a combination of price and quality. In order to gain a competitive advantage, businesses must investigate the role and impact of perceived value by customers [59].

Therefore, the following hypotheses have been formed:

Hypothesis 3 (H3). *The perceived value of service robots positively affects the intention to use them.*

The model of the research is shown in Figure 1.

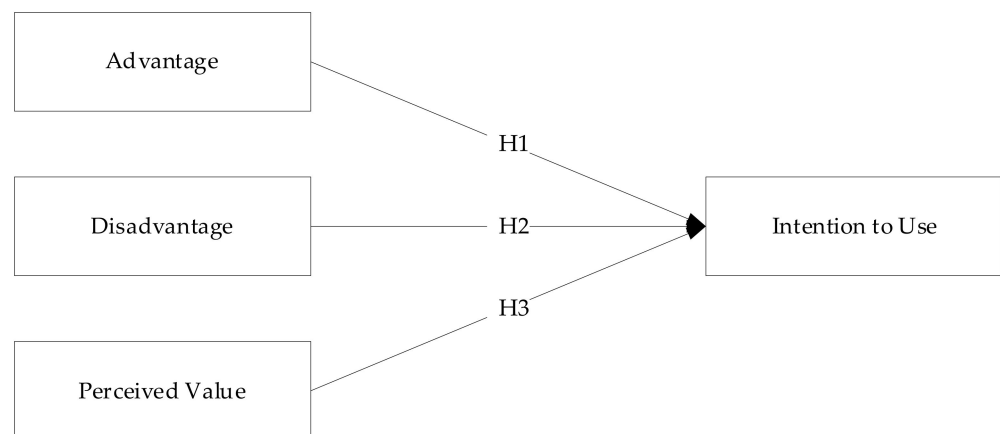


Figure 1. Research model.

3. Materials and Methods

3.1. Sample and Data Collection

The sample of the study consists of adults aged 18 and over residing in Turkey. The sample of the study consists of 1408 people selected by the convenience sampling method. Although it was planned to distribute the sample according to the population ratios in the cities, it was not fully successful because the data were collected online. However, it tried to reach participants from as many cities as possible. Sixty-six out of eighty-four cities in Turkey were reached, and data were collected from people living in these cities. Research data were collected between February 2021 and May 2021 with an online questionnaire.

3.2. Measurement Instrument

The questionnaire used in the study consisted of 2 parts; the first part included questions about some demographic characteristics of the participants. In the second part, there were questions to measure research variables Advantage (ADV), Disadvantage (DIS), Perceived Value (PV), Intention to Use (ITU) on a 1–5 Likert scale. It asked informants to indicate their degree of agreement with statements (1—strongly disagree, 3—neither agree nor disagree, and 5—strongly agree). The questionnaire was adopted from the studies listed below to measure four variables:

- Advantage (ADV); adopted from Lu et al. (2019) [60], Ivanov et al. (2018) [61], and Qui et al. (2020) [62], and based on thirteen items;
- Disadvantage (DIS); adopted from Qui et al. (2020) [62], Ivanov et al. (2018) [63], and based on seven items;
- Perceived value (PV); adopted from Zhong et al. (2020) [30] and Kervenoael et al. (2020) [64], and based on five items;
- Intention to use (ITU); adopted from Kervenoael et al. (2020) [64] and Ivanov and Webster (2019) [65] and based on seven items.

3.3. Analysis Method

The research hypotheses were analyzed using structural equation modeling. By modeling the relationships between numerous dependent and independent variables, structural equation modeling, compared to first-generation techniques, such as regression, provides a systematic and comprehensive approach to a complex research problem in a single process [66]. Structural equation modeling is extensively used in various fields, including the social and natural sciences. Unlike traditional methods, structural equation modeling considers the measurement errors of the observed variables [67].

Structural equation modeling is a broad statistical technique used to determine the linear relationships between independent and dependent variables, estimate the effects of all variables on one another, and test the relationships between observed and latent variables [68].

Structural equation modeling is a multivariate analysis method formed by combining factor analysis and multivariate regression analysis. Structural equation modeling ensures that the result obtained by testing all the observed and unobserved variables of the created model is compatible with the data at hand. If the fit indices obtained by testing the model show a fit between the model and the data, the hypotheses formed structurally are supported. If the fit indices reveal that there is no such fit, the hypotheses are not supported. First, structural equation modeling adopts a confirmatory rather than explanatory approach. While various statistical techniques other than structural equation modeling attempt to discover relationships in a data set, it verifies the compatibility of theoretically established relationships with the data [69].

There are different goodness-of-fit indices and statistical functions that these indices have, which are used in evaluating the fit of structural equation models. Among the suggested indices, the most used are chi-square statistics, RMSEA (Root-mean-square error approximation), GFI (Goodness-of-fit index), CFI (Comparative Fit Index), NFI (The Normed Fit Index), and TLI (Tucker–Lewis Index) [70]. The frequently used CFI, NFI, and TLI criteria of goodness of fit take values ranging from 0 to 1, and the closeness of the values to 1 indicates that the fit of the model is good. For RMSEA, values equal to or less than 0.05 indicate an excellent fit, values between 0.08 and 0.10 indicate an acceptable fit, and values greater than 0.10 indicate poor fit [71].

4. Results

The demographic characteristics of the participants are shown in Table 1. As shown in the table, approximately 57.2% of the participants were female, and 42.8% were male. More than half (~58.1%) of the participants were between the ages of 26–45, and more than half

(57.1%) had a university education or higher. Finally, when the accommodation preferences of the participants were examined, it was seen that ~79% prefer hotels and resorts.

Table 1. Demographic characteristics of the participants.

Gender	Freq.	Profession	Freq.
Female	802	Public/private sector worker/civil servant	315
Male	606	Public/private sector manager	111
Age		Self-employed (lawyer, doctor, accountant . . .)	215
18–25	270	Tradesman/owner	220
26–35	458	Titled personnel (Specialist, inspector, teacher...)	204
36–45	360	Retired	65
46–55	248	Housewife	48
56 and over	72	Student	230
Education		Accommodation Preference	
Primary education	99	Hotel	789
Secondary education	314	Motel	64
Associate degree	191	Resort	322
License	687	Spa	44
Master's degree	92	Villa rental	152
Doctorate	25	Other	37

Before testing the research model, the construct validity and reliability of the scales were tested. The Kaiser–Meyer–Olkin (KMO) value shows the proportion of the common variance related to the latent structure of the variables. It should be as large as possible for sampling adequacy (>0.70) [72]. After that, the construct validity and reliability of the scales used in the research were tested. For this purpose, exploratory and confirmatory factor analysis and reliability analysis were performed. The exploratory factor analysis (EFA) findings of the scales are shown in Table 2.

Table 2. Exploratory factor analysis.

Items	Fac. Load.	Skewness	Kurtosis	Mean	Std. Dev.
Advantage					
ADV1-Robots will be faster than human employees (Ivanov et al., 2018 [61])	0.603	−0.773	−0.245	3.768	1.1942
ADV2-Robots will deal with calculations better than human employees (Ivanov et al., 2018 [61])	0.760	−0.970	0.248	3.984	1.1020
ADV3-Robots will provide more accurate information than human employees (Ivanov et al., 2018 [61])	0.730	−0.678	−0.342	3.727	1.1832
ADV4-Robots will be able to provide information in more languages than human employees (Ivanov et al., 2018 [61])	0.735	−1.231	0.835	4.141	1.0860
ADV5-Robots will be more polite than human employees (Ivanov et al., 2018 [61])	0.626	−0.564	−0.825	3.589	1.3235
ADV6-Robots forever centers on customers (e.g., every time you move, the robot will adjust its head watching you). (Qui et al., 2020 [62])	0.739	−0.709	−0.327	3.762	1.1861
ADV7-Robots are always patient, no matter how many questions you ask or tasks you require. (Qui et al., 2020 [62])	0.745	−1.037	0.179	4.047	1.1401
ADV8-Customers do not need to wait as long as before during the service processes (check-in, check-out, dining, etc.) (Qui et al., 2020 [62])	0.759	−0.838	−0.012	3.906	1.1170

Table 2. Cont.

Items	Fac. Load.	Skewness	Kurtosis	Mean	Std. Dev.
Advantage					
ADV9-I am able to avoid inefficient personal contacts if I use artificially intelligent devices (Lu et al., 2019 [60])	0.702	−0.829	−0.064	3.869	1.1363
ADV10-Artificially intelligent devices, such as robots, are more dependable than human beings in services (Lu et al., 2019 [60])	0.716	−0.678	−0.333	3.732	1.1876
ADV11-Artificially intelligent devices, such as robots, are more accurate than human beings in services (Lu et al., 2019 [60])	0.803	−0.796	−0.004	3.876	1.0877
ADV12-Information provided by artificially intelligent devices, such as robots, is more accurate with fewer human errors in services (Lu et al., 2019 [60])	0.816	−0.856	0.058	3.897	1.1018
ADV13-Artificially intelligent devices, such as robots, provide more consistent service than human beings in services (Lu et al., 2019 [60])	0.793	−0.795	0.025	3.848	1.0932
<i>KMO: 0.958 Approx. Chi-Square: 9821.628 df:78 sig.:0.000 Total Variance Explained: % 64.935</i>					
Disadvantage					
DIS1-Robots can malfunction during service (Ivanov et al., 2018 [63])	0.720	−0.970	0.241	4.064	1.0711
DIS2-Robots can misunderstand a question (Ivanov et al., 2018 [63])	0.787	−0.814	−0.029	3.894	1.1112
DIS3-Robots can misunderstand an order (Ivanov et al., 2018 [63])	0.763	−0.685	−0.404	3.808	1.1621
DIS4-Robots can't do special requests/they work only in a programmed frame (Ivanov et al., 2018 [63])	0.711	−1.219	0.801	4.173	1.0560
DIS5-Robots can't understand a guest's emotions (Ivanov et al., 2018 [63])	0.707	−1.256	0.714	4.193	1.0938
DIS6-Standardized movements of robots and the manners produced by assembly line work make customers feel uncomfortable (Qui et al., 2020 [62])	0.700	−0.706	−0.411	3.805	1.1813
DIS7-I think robots limits the experience in a service environment (Qui et al., 2020 [62])	0.670	−0.618	−0.305	3.754	1.1244
<i>KMO: 0.854 Approx. Chi-Square: 3625.270 df:21 sig.:0.000 Total Variance Explained: % 63.347</i>					
Perceived Value					
PV1-Compared to the time a traditional service is provided, the use of robots in a service environment is worthwhile to me (Kervenoael et al., 2020 [64])	0.815	−0.373	−0.441	3.462	1.1146
PV2-The use of robots in a service environment delivers a satisfactory experience (Kervenoael et al., 2020 [64])	0.841	−0.479	−0.354	3.477	1.1226
PV3-Compared to the cost of service I need to pay, the use of robots in a service environment offers value for money (Kervenoael et al., 2020 [64])	0.841	−0.364	−0.469	3.429	1.1276
PV4-Using hotel robots can improve hotel service efficiency (Zhong et al., 2020 [30])	0.833	−0.476	−0.437	3.598	1.1122
PV5-I think the use of hotel robots can guarantee a uniform service quality (Zhong et al., 2020 [30])	0.764	−0.433	−0.330	3.581	1.0845
<i>KMO: 0.873 Approx. Chi-Square: 3388.347 df:10 sig.:0.000 Total Variance Explained: % 67.134</i>					
Intention to Use					
ITU1-Given the opportunity, I will use robots in a service environment (Kervenoael et al., 2020 [64])	0.821	−0.630	−0.603	3.561	1.1894
ITU2-In the near future, I will use robots in a service environment (Kervenoael et al., 2020 [64])	0.835	−0.375	−0.562	3.404	1.1727
ITU3-I'm considering using robots more in a service environment in the future (Kervenoael et al., 2020 [64])	0.872	−0.293	−0.709	3.364	1.1923

Table 2. Cont.

Items	Fac. Load.	Skewness	Kurtosis	Mean	Std. Dev.
Intention to Use					
ITU4-I intend to use service robots (Ivanov and Webster, 2019 [65])	0.873	−0.339	−0.711	3.396	1.2078
ITU5-I will be willing to recommend others to use service robots (Ivanov and Webster, 2019 [65])	0.864	−0.316	−0.730	3.320	1.2159
ITU6-I will frequently use service robots (Ivanov and Webster, 2019 [65])	0.869	−0.161	−0.866	3.234	1.2329
ITU7-I will be willing to use service robots (Ivanov and Webster, 2019 [65])	0.887	−0.275	−0.799	3.339	1.2215
<i>KMO: 0.940 Approx. Chi-Square: 8020.647 df:21 sig.:0.000 Total Variance Explained: % 74.039</i>					

As a result of exploratory factor loads, factor loads of the items were obtained above 0.50. The KMO values were above 0.70, and Bartlett's sphericity tests indicated significance for all scales. It means that the sample size was sufficient for factor analysis. It was found that each scale separately explained more than 50% of the total variance. The kurtosis and skewness values for the scales were determined between −2 and +2. It means that the data have a normal distribution.

The item with the highest average for the advantage scale was "Robots will be able to provide information in more languages than human employees", and the item with the lowest average was "Robots will be more polite than human employees". For the disadvantage scale, "Robots cannot understand a guest's emotions" had the highest average item, and "I think robot technology restricts the experience in a service environment" had the lowest average. The item "Using service robots can increase hotel service efficiency" had the highest average for perceived value. The item "Compared to the cost of service I need to pay, the use of robots in a service environment offers value for money" had the lowest average. For the intention to use, the item with the highest average was "Given the opportunity, I will use robots in a service environment", while the item with the lowest average was "I will frequently use service robots".

After exploratory factor analysis, confirmatory factor analysis (CFA) was performed for the scales. The goodness of fit values obtained as a result of confirmatory factor analysis is shown in Table 3.

Table 3. CFA goodness of fit.

Variable	χ^2	df	χ^2/df	GFI	CFI	NFI	TLI	RMS
Criterion			≤5	≥0.90	≥0.90	≥0.90	≥0.90	≤0.08
Advantage	288.887	65	4.444	0.969	0.976	0.971	0.969	0.053
Disadvantage	32.752	14	2.339	0.993	0.993	0.991	0.979	0.051
Perceived Value	6.963	5	1.392	0.998	0.999	0.998	0.996	0.031
Intention to Use	50.602	14	3.614	0.989	0.995	0.994	0.991	0.051

As a result of CFA, it was found that the scales met the acceptable goodness of fit criteria.

Reliability analysis was performed for the scales after EFA and CFA. The alpha coefficient and AVE (Average Variance Extracted) and CR (Composite Reliability) values obtained from the reliability analysis are given in Table 4.

Table 4. Reliability and validity.

Variable	AVE	CR	Cronbach' Alpha
Advantage	0.501	0.928	0.926
Disadvantage	0.444	0.846	0.847
Perceived Value	0.590	0.877	0.877
Intention to Use	0.697	0.941	0.941

As a result of the reliability analysis, alpha coefficients were obtained above 0.70. This finding shows that the scales are reliable. AVEs were above 0.50, excluding the disadvantage scale, and CR values were greater than 0.70 for all scales. The AVE of the disadvantage scale was found to be 0.444, which is very close to 0.50. These findings also show that the scales have component validity.

After determining that the scales provided construct validity and reliability, structural equation model analysis was performed to test the research hypotheses. The analyzed model is given in Figure 2.

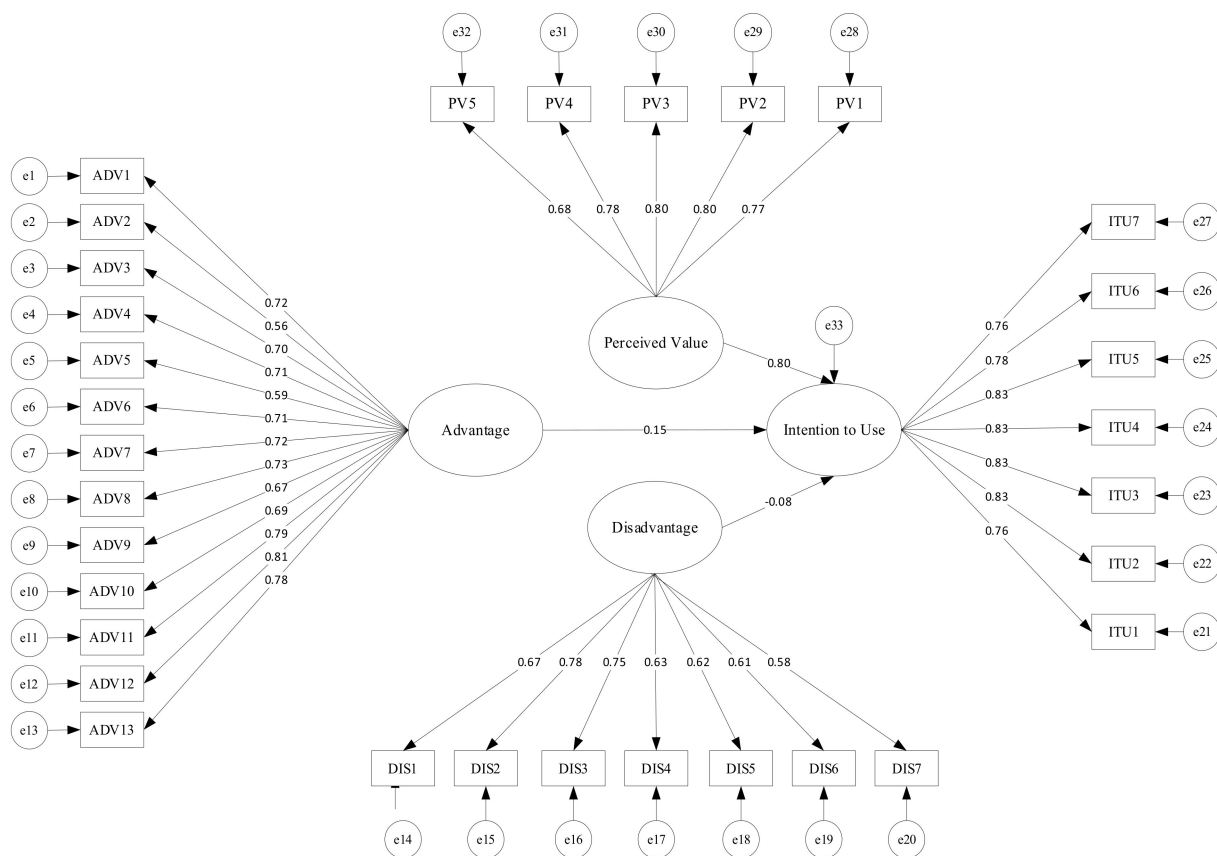


Figure 2. Structural equation model.

The model's goodness-of-fit values are shown in Table 5.

Table 5. Research model's goodness of fit.

Variable	χ^2	df	χ^2/df	GFI	CFI	NFI	TLI	RMS
Criterion			≤ 5	≥ 0.90	≥ 0.90	≥ 0.90	≥ 0.90	≤ 0.08
Research Model	2158.014	461	4.681	0.905	0.938	0.923	0.933	0.051

The structural equation model also meets the criteria for the goodness of fit.

The analysis results of the model are shown in Table 6.

Table 6. Analysis results.

Analyzed Path			B	β	SE.	CR.	<i>p</i>
Intention to Use	<—	Advantage	0.152	0.147	0.027	5.637	0.000
Intention to Use	<—	Disadvantage	−0.114	−0.084	0.028	−4.146	0.000
Intention to Use	<—	Perceived Value	0.823	0.804	0.037	22.422	0.000

As a result of the structural equation model analysis, it was found that advantage and perceived value affect the intention to use positively and significantly. In addition, it has been determined that the disadvantage has a significant adverse effect on the intention to use. As a result of the analysis, H1, H2, and H3 hypotheses were supported.

5. Discussions

This study aimed to investigate hotel customers' social perceptions and the phenomenon of service robots that will force companies to change their business models in response. Service robots entered our lives with the emergence and development of artificial intelligence, augmented reality, and similar technological concepts. Technology is changing the patterns of both social and economic life day by day. In this changing environment, companies have to keep up with change and attach importance to innovation for sustainability. One of the sectors deeply affected by technological change is the tourism industry. The use of digital technologies as a productivity tool in the service sector is not new. Hospitality companies have started to use software, such as customer relationship management (CRM) and enterprise resource planning (ERP), almost simultaneously with other sectors. Electronic commerce activities are used very actively in this industry. However, in a way that people are not used to, front-line workers being machines, and service delivery to customers by robots is a relatively new phenomenon. There are very few studies on service robots, which are seen as a critical innovation in the tourism sector in the literature, and the subject needs to be examined from many perspectives.

The study's first finding showed that hotel customers' perceptions of advantage regarding service robots increased their positive intention to use robots. This finding is consistent with studies in the literature. In particular, COVID-19 has affected people's acceptance of robots and high-tech services to minimize physical contact [13]. In addition, it was thought by customers that robots can perform services without errors. From a marketing perspective, customers saw service robots as fashionable [55]. Furthermore, customers thought that waiting times would be shortened, which would create comfort compared to the services they receive from human employees (e.g., check-in/check-out services, carrying luggage to rooms, etc.) [37]. In addition, according to customers, robots working in jobs, such as concierge, room service, and reception, performed complex operations more accurately [55]. For example, service robots will fulfill the order of a customer who wants a snack at any time of the day [34]. Therefore, robots can operate without errors in transactions that are important for customers in terms of timing (for example, wake-up service). Customers who enjoyed using robots thought that service robots were beneficial for them, which positively affects their intention to use service robots [73].

The second finding of the study revealed that hotel customers' perceptions of disadvantage regarding service robots negatively affected their intention to use robots. Customers who have technology anxiety may be especially worried and afraid about using new technology [10]. There may be customers who prefer to chat with humans rather than robots. Such customers find it more friendly for a human to greet and chat in the lobby than for a robot to do these things [74]. Customer's refusal to accept the technology resulted in their inability to take advantage of the potential advantages of service robots [75,76]. Some customers thought that when the use of service robots becomes widespread, people will

be unemployed. Therefore, these customers exhibited negative attitudes towards service robots [33].

The third finding of the study showed that hotel customers' perceived value of using robots made them more willing to use robots. For example, the fact that robot waiters equipped with artificial intelligence recognize customers and greet them by name created a positive perception of the service provided to customers [77]. A service robot that addressed customers with a smile and polite language was perceived by customers as more friendly and approachable [34]. During interaction with customers, robots can detect their facial expressions, make inferences about their emotions, and respond to them according to their emotional state [39]. Human workers will not be as successful as robots at hiding their own emotions. Therefore, they can reflect their negative personal feelings with their body language, even if not verbally. It means that robots may be more successful in emotional labor. In addition, the ability of a robot to speak many languages prevents misunderstandings because customers do not know foreign languages and make customers feel more comfortable and valuable.

According to the study findings, it can be said that hotel managers must carry out innovation activities related to service robots in terms of sustainability. However, the investments to be made in this regard are sensitive enough to be affected by many variables. Many factors, such as the shapes of robots, the services they can perform, etc., are essential. For example, the perception of robots may differ according to age and gender. Studies have shown that young people adopt this type of service more, while women are more skeptical of robots. Males prefer female robots more. Children, on the other hand, find service robots entertaining [73]. Therefore, these study results advise hotel industry managers to conduct extensive research and understand their customers' preferences in detail before making an investment decision regarding service robots. In addition, practitioners should cooperate with academics researching the subject.

6. Conclusions

Today, one of the most significant advances in the usage of service robots is in the tourism industry. With digitalization becoming an ordinary (even necessary) phenomenon, the patterns in our social life have changed. Human relations have moved to different dimensions with digital technologies, and there is no doubt that the crises we experience (COVID-19, climate crises, etc.) have a significant impact on this. Technological developments have been reflected in our lives as the precautions we took in the face of crises, and they also changed the patterns of social life.

Companies may view their investments in this technology as significant risks. In this research, we tried to reveal some of the benefits of this technology to companies. For this purpose, we determined the customer's intention to use the services provided by robots, which is an essential phenomenon in the hospitality industry, as a dependent variable. There are undoubtedly many variables that can affect customers' intentions to use a service robot. In this study, based on the relevant literature, we determined three types of perceptions that we think may affect the use of service robots as independent variables and created our research model accordingly. These perceptions were the perception of advantage for customers to think that using service robots is more advantageous, the perception of disadvantage that expresses the adverse effects of using service robots, and finally, the value perceived by customers as a result of using service robots.

As a result of our analysis, we found that all three variables affect hotel customers' intention to use service robots. Among these variables, the perceived value and perception of advantage affect the dependent variable positively, while the perception of disadvantage negatively affects the dependent variable. The relevant literature emphasizes that if customers have a high perception of value for a technological service and believe that that service is more advantageous, they prefer and want to use the service. On the contrary, if customers believe that a technological service has some disadvantages, they do not use that service. As a result of the analysis, we concluded that most participants consider service

robots to be advantageous and value-creating components. The study results showed that the perception of disadvantage that can be encountered in this type of service was low. We recommend that hotel management companies adapt to this environment to survive in the changing technological environment and turn the change created by technology in customer perception into an opportunity. As a result of the study, we believe that hotel companies should display a more willing and innovative approach to technological investments, especially service robots.

In the literature review conducted at the beginning of this study, we found very few studies examining the study's variables. We think that there is an important gap in the literature on the subject, and in this respect, we believe that the research model created in our research is original. We hope that this study will make an essential contribution to the existing literature. We also believe that the findings of the study will benefit all hospitality companies.

We can say the following regarding the study's limitations and future studies: The first limitation of this study is the sampling frame and data collection method. Since it was impossible to reach a complete list of people living in Turkey and receiving hotel services, it was not possible to create a complete sampling frame. Instead, we collected data through an online survey by reaching hotel customers that were reachable from all cities in Turkey. The pandemic has had an impact on the production of an online solution as a data collection method. However, we believe that the sample size is the strength of the study. More detailed random sampling methods can be used in future studies. In addition, we can say that the sample size of this study is relatively large compared to similar studies.

In addition, we focused only on customer perceptions, that is, on the main variables of the study, and conducted our analyzes in this direction. We did not analyze the effect of participants' demographic characteristics, such as age and gender, on the dependent variable. The reason for this was that some studies have examined such demographic variables in the literature, and we wanted this study to focus more on perceptions. Future research can be designed to examine how perceptions change according to demographics. In particular, research can be conducted on the customers of hotel companies segmented according to demographic characteristics and serve a specific age group or a specific demographic feature.

Finally, this study makes an indirect reference to innovation in the hospitality industry. In future research, it is suggested that innovation, which is not included in this research model, should be directly included in research models as a research variable. In addition, it is thought that examining the effect of high technology use policies is very important in terms of the relevant literature.

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