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Tourism Marketing in the Digital Age: AI Service Robots Impact on Touristic Experiences

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Master in Marketing

Supervisor:
PhD Álvaro de Borba Cruz Lopes Dias, Associate Professor with Habilitation,
Department of Marketing, Operations & General Management
ISCTE Business School

October, 2024

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Department of Marketing, Operations & General Management

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Resumo

O objetivo desta tese é examinar o papel dos robôs de serviço baseados em IA na melhoria da experiência dos turistas e, mais especificamente, identificar os motivos de interesse e aceitação dos mesmos por parte dos utilizadores nesta área. Com base num modelo modificado do modelo S-RAM, esta investigação explora o papel de fatores hedónicos, como a *cuteness* e a humanidade, e algumas caraterísticas funcionais, como a perceção de utilidade ou a expetativa de desempenho. Depois de estudar os dados recebidos da amostra, o investigador descobriu que a aceitação pode ser prevista por duas variáveis independentes: expetativa de desempenho e utilidade percebida. Por outro lado, a *cuteness* tem um efeito apenas nas pessoas que nunca tinham interagido com um robô de serviço. O estudo aborda o processo de aceitação da tecnologia, argumentando que devem ser consideradas duas fases no funil de comportamento do utilizador, interesse e aceitação, influenciados por diferentes tipos de fatores. Estas conclusões são úteis para os gestores do turismo que pretendem integrar os robôs de serviço nas suas operações, uma vez que identificam uma série de obstáculos, o mais importante dos quais é a necessidade de assegurar uma integração adequada e equilíbrio correto entre estética função. Este estudo contribui para a literatura existente, explorando a aceitação da tecnologia no contexto do turismo, complementando assim os dois modelos, TAM e sRAM no contexto de serviços turísticos.

Palavras-chave: Robôs de serviço, marketing turístico, aceitação da tecnologia, IA no turismo, experiência do utilizador

JEL Classification System: M31; Z33

Abstract

The aim of this thesis is to examine the role of AI-based service robots in improving the tourist experience and, more specifically, to identify the reasons for user interest and acceptance in this area. Based on a modified model of the S-RAM model, this research explores the role of hedonic factors, such as cuteness and perceived humanity, and some functional characteristics, such as perceived usefulness or performance expectancy. After studying the data received from the sample, the researcher discovered that acceptance can be predicted by two independent variables: performance expectancy and perceived usefulness. On the other hand, *cuteness* only influences people who have never interacted with a service robot before. The study addresses the technology acceptance process, arguing that two phases in the user behavior funnel should be considered, interest and acceptance, influenced by different types of factors. These findings are useful for tourism managers looking to integrate service robots into their operations, as they identify a number of obstacles, the most important of which is the need to ensure proper integration and the correct balance between aesthetic and functionality. This study contributes to existing literature by exploring the acceptance of technology in the context of tourism, thus complementing the two models, TAM and sRAM in the context of tourism services.

Keywords: Service Robots, Tourism Marketing, Technology Acceptance, AI in Tourism, User Experience

JEL Classification System: M31; Z33

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1. Introduction

In this thesis introduction, we will address the study's objectives, contextualizing the research problem and its relevance. We will look at what generally already exists on the subject and identify a gap worthy of being studied, which will act as the basis of the thesis. A series of research questions will be formulated, with the intention of fortifying the foundation of the dissertation. Having said that, the research topic is "Tourism Marketing in the Digital Age: AI Service Robot's Impact on Touristic Experiences". This topic addresses the results of an increasingly technological world, which seems to be heading more and more towards the automation of several tasks. Artificial intelligence (AI) has become a widespread presence in several industries such as healthcare, banking, entertainment, and automotives. This is mostly attributed to its advantages in terms of increased productivity, reduced costs for staff replacement, and accuracy and efficiency when performing tasks. This fast and widespread use of AI has had an impact on the subject of service robots, as their growth rate is much faster than even the robotic manufacturing market (Y. Lee et al., 2021). This is sure to have an impact within several organizations and change the world as we know it today. In fact, service robots are already substituting and improving the human workforce (Y. Lee et al., 2021), as their highly efficient nature allows them to perform dual functions, and therefore take care of some repetitive and monotonous service requests (Fan et al., 2022). This is being felt in the tourism business as well, as hotels and restaurants have begun to replace some of its workforce with automated service robots, with all the aforementioned advantages in mind, while looking to keep the same service quality to guests (Y. Lee et al., 2021).

However, replacing human employees with service robots in tourism and hospitality settings, that are known for their intense human interactions, not only modifies the nature of the service experience to include human-robot interactions, but it may also have a significant impact on customer behavior and attitudes (Tussyadiah et al., 2020). This is what we will look to comprehend throughout the thesis, as the presence of service robots in this domain is a relatively new topic (Tussyadiah et al., 2020), and therefore there is a lot of opportunity for contribution.

With these developments in mind, tourism is, like all other fields, sure to be affected, and marketing in this area as well. Therefore, the interest in this topic lies in looking at the travel industry with a specific focus on the impact of service robots on customer experiences, the customer´s acceptance of service robots, desire or disinterest in having touristic experiences which involve service robots, as well as conclude upon possible shifts in marketing within this field.

Preparing for a future that, in fact, is already here, is key to success. Some of the studies already made, which will be further developed in the literature review, look at several characteristics and establish different connections between a plethora of different variables. Most studies which use the base model we will use, the service robot acceptance model (Wirtz et al., 2018), explore both sides of hedonic experiences and functional experiences, and draw conclusions on their widely different topics. Through a thorough literature review, the objective is to use the studies which have already been made and conclusions which have already been drawn and expand on it. In order to innovate, we developed a conceptual model, which can be seen in the literature review (Figure 2) of this work, that contemplates different variables from several articles and different models, with the goal of reaching a conclusion on if there is a difference between the stage of interest and acceptance of service robots in the touristic field, and what are the constructs that have the biggest impact on these two variables.

To achieve this goal, three questions were prepared that we intend to answer with this research:

RQ1: How does cuteness influence interest and acceptance of service robots among different user groups?

RQ2: Do people have hedonic or functional motivations on the use of service robots in their touristic experiences?

RQ3: To what extent does perceived usefulness contribute to shaping users' interest in service robots compared to its impact on acceptance?

2. Literature Review

2.1 Evolution of AI Service Robots

A new topic arose in 1956, when the term "artificial intelligence" was first introduced by scholars. This term would then go on to experience a long development period of over 70 years (Zhang & Lu, 2021). AI has had an incredible rapid development in the last couple of years, being applied to several areas and now being an impactful proponent of our everyday lives. Following the 1990s, the use of robots in the production sector progressively evolved to the service sector, leading to a rapid development of service robots (Sun & Wang, 2022). This was possible due to many recent developments in artificial intelligence and machine learning, which allowed robots to now be able to detect and react to their surroundings, making way for their application outside of contained production areas and expand into new fields, such as the service field (Savin et al., 2022). These changes were, in turn, potentiated by an advancement in complementary technologies, like AI and cloud computing, as well as increased computing capabilities, lighter materials, and lower hardware costs (Savin et al., 2022). The market for service robots is now growing worldwide, driven mainly by Japan, whose market for service robots is expected to grow a lot between now and 2035 (Lechevalier et al., 2014). It is now possible to see service robots in several fields. When it comes to the touristic industry, we can look at the example of several restaurants around the world, where robot chefs and greeters have been transforming traveler's experiences, by cooking and welcoming them in a different way (Huang et al., 2023).

However, there is a looming danger in all of this. The topic of human replacement of frontline employees by service robots is one over which a lot of literature delves upon, as service robots are able to work under the economic principle of economies of scale, while frontline employees are not scalable at all, as every new hire comes with ongoing costs. (Wirtz et al., 2018).

2.2 Base Definitions

Firstly, looking at the base concept for the entire thesis, it is possible to say that AI is the general term for the science that simulates human intelligence using computers, and it involves teaching machines to mimic human cognitive processes like learning, judgment, and decision-making (Zhang & Lu, 2021).

Secondly, it is also important to look at the definition of service robots, a crucial part of what we will look to investigate, as although AI is sure to be used in tourism in many ways and appear to the customer in many shapes and forms, (such as chatbots, VR tourism, amongst others), AI driven service robots are the main focus of the study. Therefore, it is possible to say that service robots are adaptable autonomous machine interfaces, which are capable of interacting, communicating, and providing services to consumers (Wirtz et al., 2018). They can be humanoid (anthropomorph) or non-humanoid in terms of their appearance. A humanoid is a human-like service robot, and a non-humanoid has the physical look of a machine. Lastly, these service robots can perform cognitive-analytical tasks and emotional-social tasks (Wirtz et al., 2018).

Looking at evaluating touristic experiences with service robots in places such as hotels or restaurants, it is important to look at the concept of customer-journey as a base concept, which includes three stages of interaction: the pre-service, service, and post-service encounter stages (Manthiou & Klaus, 2022). A consumer's path with an entity throughout the course of the whole purchase cycle, spanning the previously mentioned touchpoints, may be conceptualized as a customer journey. It is a dynamic process, which means that outside variables and events from the past may have an influence on its outcome. Companies can only control a portion of the touchpoints that the customer experiences (Lemon & Verhoef, 2016).

2.3 Interest in Having Service Robots in Touristic Experiences and Service Robot Acceptance Model

The Technology Acceptance Model (TAM), introduced by Davis (1989), serves as a foundation for understanding the factors that influence users' decisions to accept new technologies. The TAM, in short, postulates that perceived usefulness and perceived ease of use are critical determinants of technology adoption (Davis, 1989). In general, TAM is all about functional motives for the use of technology, presenting arguments such as the cost-benefit theory and self-efficacy theory (Davis, 1989).

In complement, and at the same time in a contradictory manner, (Wirtz et al., 2018) presented the SRAM (Service Robot Acceptance Model). The Service Robot Acceptance Model was developed by (Wirtz et al., 2018), and it helps understand users' interactions with robots in service situations, making it the perfect base model from which to build upon. The SRAM postulates that consumer acceptance of service robots depends on three sorts of elements: functional, social-emotional and relational. When looking at the variables within the dimensions (fig.1), we can see that the SRAM draws from the Technology Acceptance Model and uses three variables for "Functional elements" (Perceived ease of Use, Perceived Usefulness; Subjective Social Norms); the model also has three "social-emotional" variables which are Perceived Humanness, Perceived Social Interaction and Perceived Social Presence; the variables used to compose relational elements are Trust and Rapport. The drawn conclusions from this model, in sum, were that the relationships established between these sets of elements and customer acceptance of service robots were, in fact, positive, meaning that emotional-social and relational elements also play a roll in the acceptance of service robots (Wirtz et al., 2018) and that customer needs are essential when looking at the achieving harmony across all three dimensions (Fuentes-Moraleda et al., 2020).

When taking the SRAM into the touristic sector, it is important to denote that the touristic experience is often just that, an experience, rather than a goal or a solution to a problem, and therefore service delivery can occur at several touchpoints. Consumers who are looking for enjoyable touristic experiences usually have high expectations for enjoyable social presence, engagement and sharing of vibrant emotions (Fuentes-Moraleda et al., 2020).

In examining the adoption process of service robots in touristic settings, this study found that it is essential to distinguish between two critical stages of the consumer's "funnel": interest and acceptance. Interest is often a neglected emotion in studies, but it is a fundamental one, representing the initial phase, as it is a source of intrinsic motivation to develop further seeking of information (Silvia, 2001) or, in this case interaction with the service robots. This manifests itself through acceptance, which marks a more mature phase of the adoption process, where users make a conscious decision to integrate service robots into their experiences based on functional motivations, functional elements and social-emotional elements (Davis, 1989; Wirtz et al., 2018). In this study, and specifically in regards to the acceptance of service robots, our focus will be on re-testing one of both the social-emotional elements (hedonic) and functional elements, as well as test a new variable within this model for each of these types of elements (cuteness and performance expectancy). The relational elements were not studied, as they were the least mentioned by touristis when describing their interactions with robots in this field in (Fuentes-Moraleda et al., 2020)'s study.

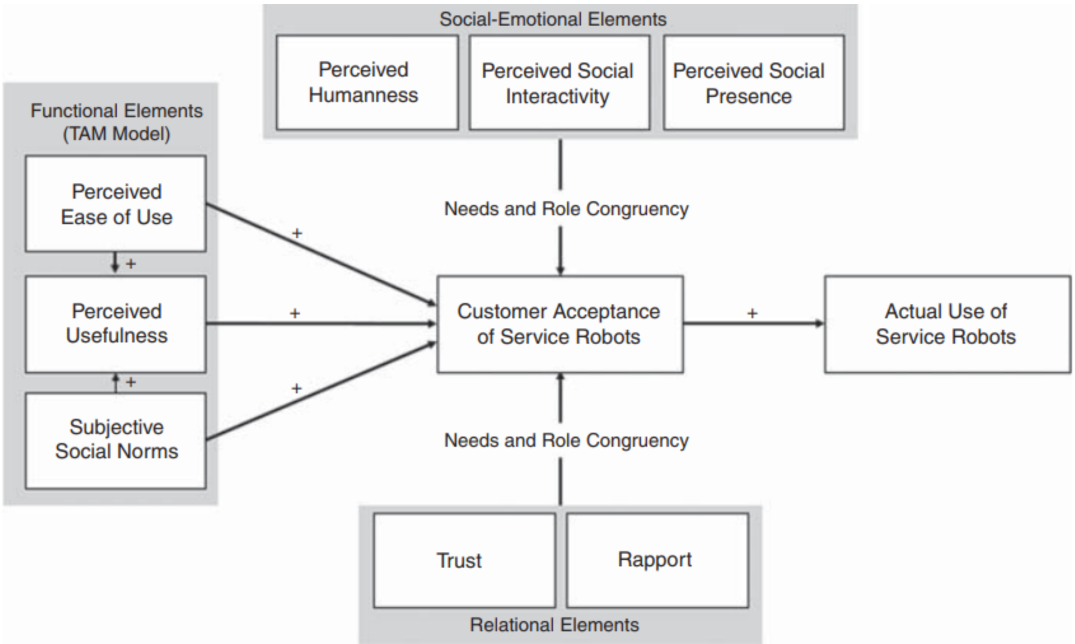

Figure 1 - Service Robot Acceptance Model (Wirtz et al., 2018)

2.4 Hedonic Factors

2.4.1 Cuteness

Cuteness is a hedonic factor which will act as a representative of the customer's cognitive experience, one of the most fundamental influencers of human behavior (Steinnes et al., 2019), and the most mentioned experience felt by consumers in (Huang et al., 2021)'s survey. There is not a lot of literature regarding the direct relation between this construct and service robots, and therefore it is worth studying.

Something being cute implies that humans will have a tendency to look at it longer, and studies show that the emotional feeling of something being cute is normally related to a mix of feelings, both caring impulses and aggressive responses, such as wanting to pinch, squeeze, or bite the target and the act of clenching hands and teeth (Steinnes et al., 2019).

In touristic experiences, cuteness relates to the way in which guests think of the service the robot is providing as "cute", an attractive characteristic of having service robots in the frontlines. This cuteness often comes from the robot having a childlike voice, its physical appearance and expression, and sometimes also by its uncoordinated movements (cuteness by contrast of its highly developed technology and its somehow silly behaviors) (Huang et al., 2021). In a study led by (Guo et al., 2024), it was concluded that consumers are more willingly going to interact with cuter service robots, specifically when it comes to hedonic services, such as a touristic experience.

Cuteness is also shown to be able to increase customer's tolerance of service failure (Steinnes et al., 2019), in low severity condition's and low-time pressure conditions only (Lv et al., 2021). Therefore, it can be concluded that having cuteness (baby-like characteristics such as softness, small limbs, round shapes in head and body, large eyes and a large head) (Golonka et al., 2023) as a component of a service robot is a powerful tool when looking for customer acceptance. This is also reflected in (Joshua Paul Dale et al., 2017), who states that cuteness is a significant technique for gaining customer acceptance, as humans are more likely to approach a cute object.

With this in mind, as well as the research questions, this study proposes a few advancements: First of all, and focusing on a lack of literature on what is clearly an important variable, to further study this subject in regards to the topic of Interest in Having Service Robots in Touristic Experiences, as well as their Acceptance. Secondly, testing this in different user groups, as research suggests that perception on something, in this case service robot cuteness, is both determined by sensory input, individual expectations and prior knowledge (Kok et al., 2013).

All of this led us to the following hypothesis, tested on two different user groups:

H1Y: Cuteness positively influences interest in having service robots in touristic experiences

H1N: Cuteness positively influences interest in having service robots in touristic experiences (individuals who have not interacted with one)

H2Y: Cuteness positively influences service robot acceptance

H2N: Cuteness positively influences service robot acceptance (individuals who have never interacted with one)

2.4.2 Perceived Humanness

An integral part of the service robot acceptance model, perceived humanness is a variable which is integrated into the social-emotional dimension and has an impact on the acceptance of service robots according to the model (Fuentes-Moraleda et al., 2020). With this variable we plan to retest this in both the generation of initial Interest In Having Service Robots in Touristic Experiences and Service Robot Acceptance in this specific field.

Perceived humanness is related to anthropomorphism, the condition of looking and acting like a human. In the service industry, additionally to being cute, looking and/or acting like a human goes a long way in establishing meaningful social interaction. However, contrary to cuteness, overly simulation of human appearance may create a feeling of expectations that are high, and therefore can easily cause disappointed customers, because the more human-like a robot looks, the more human the customer expects it to behave. Overly human likeness can also scare away some customers, meaning that having small details which make it look like a robot is also important (Wirtz et al., 2018). This is related to the "Uncanny Valley" theoretical concept, that tells us that if the robot's appearance and actions are made more human–like, people's emotional response will be increasingly better, until a certain point where revulsion occurs (Rau et al., 2010).

Focusing on improving human interaction and human-like behavior is proven to enhance customer satisfaction, and ultimately, continued acceptance/adoption of service robots in service sectors which can be related to touristic experiences, such as restaurants (Ku, 2024). (Wong A. & Wong J., 2024)'s study also emphasizes the critical role of anthropomorphic influences of appearance on robot interaction intention and engagement, generation of positive feelings and positive word-of-mouth among museum visitor's who interacted with service robots.

This led us to our third and fourth hypothesis, based on understanding if perceived humanness actually leads to interest in having service robots in touristic experiences in general and to their acceptance:

H3: Perceived humanness positively influences interest in having service robots in touristic experiences

H4: Perceived humanness positively influences service robot acceptance

2.5 Functional Factors

2.5.1 Perceived Usefulness

Moving on to functional factors, and looking specifically at Perceived Usefulness, this variable is connected to a customer's cognitive experience and influences his intention to use a new technology (Wirtz et al., 2018), such as a service robot. Perceived usefulness of service robots is related to being able to obtain a practical advantage in the eyes of the customer, such as enjoyment (McCartney G. & McCartney A., 2020), or how that particular technology would enhance their performance (Davis, 1989).

This variable is an integral part of the Technology Acceptance Model (Davis, 1989), and it was chosen, over perceived ease of use as it is the closest tied variable to anthropomorphism (Li & Wang, 2022) (which also affects cuteness). Therefore, in order to have a homogenic model which doesn´t disperse too much, we decided upon this variable over the other ones in the functional elements of SRAM (Perceived Ease of Use; Subjective Norms) (Wirtz et al., 2018).

Prior research shows a significant positive effect of perceived usefulness on engagement, interest in interacting with and continued use of service robots in museum settings (Wong A. & Wong J., 2024), as well as intention to revisit service robot restaurants (Seo & Lee, 2021). This aligns with (Davis, 1989)'s TAM. On the other hand, one study found that in the service sector, perceived usefulness significantly affects customer's acceptance/adoption of service robots for credence service settings (like a hospital), but it is not significant for experience service settings, meaning that for touristic experiences, it should have less to no impact (Park et al., 2021).

With these contradictory findings in mind, this study decided to re-test this construct for the tourism sector, and the following hypothesis were developed:

H5: Perceived usefulness positively influences interest in having service robots in touristic experiences

H6: Perceived usefulness positively influences service robot acceptance

2.5.2 Performance Expectancy

When looking at Performance Expectancy, this variable refers to the consumer's belief that the adoption of service robots will increase the ability and competency of satisfying their own needs (Y. Lee et al., 2021). Performance Expectancy is related to a subjective form of performance, over which there is in fact a proven link between perceived performance and satisfaction, but only when placed in an individual value system (Wirtz & Mattila, 2001). Performance expectancy is also found to be related to the ethical perceptions of the use of AI (Figueroa-Armijos et al., 2023).

(Chiang & Trimi, 2020)'s study showed that, in their case, customers' trust and confidence, and therefore future acceptance in service robots decreased when their actual performance did not meet the expectations of the hotel's guests. This further shows the importance of testing this variable and realizing its true value in the tourism sector on the interest in having service robots in touristic experiences and acceptance of service robots.

Being a variable which is highly regarded in the UTAUT model (Venkatesh et al., 2003), the plan is to associate it more with (Wirtz et al., 2018)'s model by implementing it into our model as the new functional construct and test the validity of the following hypothesis:

H7: Performance expectancy positively influences interest in having service robots in touristic experinces

H8: Performance expectancy positively influences service robot acceptance

2.6 Conceptual Model

The literature review led us to create the following conceptual model, based on the hypothesis (Figure 2):

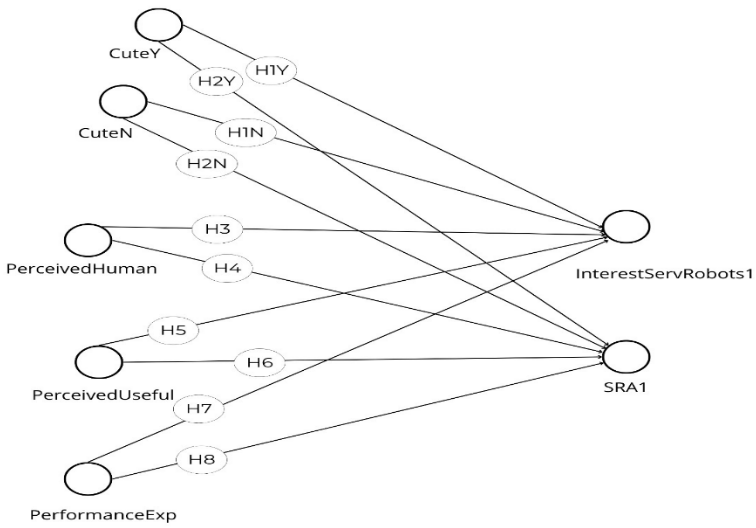

Figure 2 - Conceptual Model

3.Methodology

In order to answer the research questions, a deductive approach was taken, as we took definitions, as well as conclusions and theoretical positions drawn by previous studies, and tested if a different group of people (varied age groups) impacted the relationship between the acceptance of service robots and the hypothesis already tested in other studies and that integrate SRAM, as well as the ones we decided to use as representatives and whose relevance explanation was given in the literature review. The objective was to then conclude if people have a desire or disinterest in having service robots in their touristic experiences.

A multi-group analysis was, therefore, conducted. In terms of the type of research being conducted, a mix between analytical and predictive research happened, as we collected and analyzed data, which also allowed us to speculate intelligently on the future of marketing in this field, caused by the voice and will of the customer, which dictates market needs and therefore, shapes marketing. The goal here is to establish business outcomes from customer needs.

3.1 Sample

By using a questionnaire survey and a convenience sample, this study looked to gather insights into the acceptance of service robots, as well as people's interest's in having them in their touristic experiences. We managed to gather 213 responses, out of which 183 of them were usable, as the rest were incomplete. All of the respondents were over 18, most of them being aged between 31 and 55 (49,7%). Most respondents were women – 131 – (71.2%), full-time employees (71%) and with an earning between 1000€ and 1400€ (29,5%) average individual liquid salary. Most respondents either had secondary school as their highest level of education (41,5%), with a bachellor's as a close second (37,7%). Table 1 - Characterization of the SampleTable 1

Out of our sample of 183 people, 141 had not yet interacted with a service robot at the time of the survey (77%). Out of the remaining 42 people who had interacted with service robots before, most of them claimed to have had this experience in restaurants (76,1%). - Table 2

Table 1 - Characterization of the Sample

Demographic data		Frequency	Percentage (%)
What is your age?	18-30	49	26,7
	31-55	91	49,7
	55+	43	23,6
	Total	183	100,0
What is your gender?	Female	131	71,2
	Male	51	27,8
	Other	1	0,5
	Total	183	100,0
What is your current occupation?	Employed full-time	130	71,0
	Employed part-time	3	1,6
	Retired	14	7,7
	Student	13	7,1
	Student-worker	15	8,2
	Unemployed	8	4,4
	Total	183	100,0
What is your monthly salary?	<1000€	38	20,8
	>2000€	25	13,7
	1000-1400€	54	29,5
	1400-2000€	46	25,1
	I don't have a salary	20	10,9
	Total	183	100,0
What is the highest level of education you have completed?	Bachellor's	69	37,7
	Doctorate	1	0,5
	Less then secondary school	10	5,5
	Master's	27	14,8
	Secondary school	76	41,5
	Total	183	100,0

Table 2 - Interaction with Service Robots

		Frequency	Percentage (%)
Have you ever interacted with a service robot during a touristic experience?	No	141	77,0
	Yes	42	23,0
	Total	183	100,0
If yes, then in what context?	Restaurant	32	76,1
	Airport	5	11,9
	Telephone Assisant	1	2,4
	Hotel	2	4,8
	Cleaning Robot	1	2,4
	Shopping	1	2,4
	Total	42	100,0

3.2 Measures

The questionnaire was divided into three parts: Firstly, the demographic questions, which made it possible to characterize the sample.

As one of the variables was cuteness, this required knowledge of a service robot's appearance. In order to accommodate both the participants who had interacted with a service robot and those which had never had that experience, we decided to use branching in our survey design. Branching allowed us to, unaware to the respondent, organize the initial part of survey in a way that he could answer the items related with the variable “cuteness”, whether he had interacted with a service robot or not. We did this by showing those who had not interacted yet an image of a service robot and answering the same exact questions. This was done for this variable only, as the survey converged in the remaining questions, because it didn’t require having experience with a service robot. Using the branching method also allowed us to have a follow-up question (Norman, 2002), to the people who answered “yes” to if they had an interaction with a service robot or not, giving us more insight into how they had interacted with it.

For all the variables in the concept model, validated scales were used. The questionnaire was fully done in English and translated into Portuguese, keeping in mind both linguistic and psychological meaning (Hambleton et al., 2006). A Likert-type scale (1 – Totally Disagree to 5 – Totally Agree) was used to measure the items in the questionnaire, which was created using Qualtrics Survey Software and analyzed using SPSS and SmartPLS.

3.2.1 Cuteness

Cuteness is the emotional feeling that makes humans look at things longer and leads to both caring impulses and aggressive responses, such as wanting to pinch, squeeze, or bite the target and the act of clenching hands and teeth (Steinnes et al., 2019). It is related to having baby-like characteristics such as softness, small limbs, round shapes in head and body, large eyes large head) (Golonka et al., 2023). To measure this construct we used exactly the same items as (Huang et al., 2024), which are the following: (1) The service robot was cute; (2) The service robot was adorable; (3) The service robot was endearing; (4) The service robot had a loveable appearance.

Like mentioned before, this variable was tested separately between people who had already interacted with service robots and people who had not.

3.2.2 Perceived Humanness

Perceived Humanness reflects the service robot’s ability to look and / or act like a human (Wirtz et al., 2018). The measures used for this construct in this study refer from (Belanche et al., 2020) and were the following: (1) "I find it better overall if the appearance of the robot is very human like"; (2) "I find it better overall if the appearance of the robot is very mechanical".

3.2.3 Performance Expectancy

Performance Expectancy is the consumer's belief that the adoption of service robots will increase the ability and competency of satisfying their own needs (Y. Lee et al., 2021). In this study, we measured this construct with 4 items, adapted from (Walton et al., 2012)'s study, which measure performance expectancy of mobile internet: (1) I find that service robots are useful in touristic experiences; (2) Service robots increase my chances of having a good experience; (3) Service robots help achieving things more quickly (such as serving food at a restaurant or carrying bags up the stairs in hotels); (4) Service robots are more productive then human employees in touristic related businesses.

3.2.4 Perceived Usefulness

In this study, perceived usefulness of service robots is related to being able to obtain a practical advantage in the eyes of the customer, such as enjoyment (McCartney & McCartney, 2020), or how a particular technology would enhance job performance (Li & Wang, 2022). It was measured by 3 items, adapted from (M. K. O. Lee et al., 2005), which are the following: (1) Using service robots will improve my experience with a touristic event.; (2) The advantages of using service robots in tourism outweigh the disadvantages; (3) Overall, using service robots in touristic experiences will be advantageous.

3.2.5 Interest in Having Service Robots in Touristic Experiences & Acceptance of Service Robots

We also decided to test these two constructs on a Likert type-scale.

Interest in having service robots in touristic experiences was measured using the item (1) How interested are you in having service robots assist in your touristic experiences? on a Likert type-scale, where 1 – Not interested at all and 5 – Extremely interested.

As for the Acceptance of Service Robots, being the founding theory of this paper tells us, in sum, that the relationships established between its three sets of elements and customer acceptance of service robots were, in fact, positive, and that customer needs are essential when looking at the achieving harmony across all three dimensions (Fuentes-Moraleda et al., 2020). With this in mind, one item was used, as a lot of the variables themselves used in this study were also used in the Service Robot Acceptance Model (Wirtz et al., 2018). The item was (1) Based on your experience (or what you imagine), how likely are you to accept service robots in future touristic experiences?, and it was measured on a Likert-Type scale, from 1 to 5, where 1 – Very Unlikely and 5 – Very Likely.

3.3 Data Collection

Before starting to distribute the survey, a pre-test was done on seven academics, and their feedback was collected and used to make the necessary changes for everything to be aligned with the goal. This survey was created using Qualtrics Survey Software and analyzed using SPSS and SmartPLS. As previously mentioned, a translation was applied so that the questionnaire could be distributed in both Portuguese and English. The final version of the questionnaire was mostly spread between several social media platforms, as the increased visibility of social media can many times lead to higher engagement rates and potentially more responses to our survey, aswell as facilitate simple interaction pathways between researchers and potential participants (Özkent, 2022), and it had the duration of 30 days (August 3rd to September 3rd)

The used model was developed under the logic of SEM (structural equation modelling), which is a method used to allow researchers to model and estimate complex relations between several independent and dependent variables at the same time (Hair et al., 2021). For our sources of collection, we have primary data, collected via survey, as well as secondary data from the literature review.

4. Results

4.1 Data Analysis

As mentioned before, and because there was a need to analyze both the measurement characteristics of constructs and their interactions at the same time, we used Structural Equation Modelling (SEM). In particular, partial least squares (PLS) was used, which is a causal-predictive approach to SEM, used to provide important insights into the strength and significance of the model's relationships (Sarstedt et al., 2021). To do this, Smart PLS4 software was used (Ringer et al., 2024). Importance Performance Matrix Analysis (IPMA) was another technique that was applied, in order to be able to rank the importance of the constructs towards the model's overall performance in practical applications (Nadella et al., 2024). Finally, SPSS version 29 was used to do the demographic data analysis.

4.2 Model Validity and Results

The analysis and interpretation of data was done in two major steps: firstly, the reliability of metrics used, the validity and the quality of the measurement model were studied; and only after this we studied the hypothesis.

The indicators of reliability, convergent and discriminant validity and internal consistency reliability were used to see the validity of the used measurement model (Cheung et al., 2024). By analyzing the output, we can see that the standardized factor loadings of all items are greater than 0,5 (at a minimum value of 0.79) and were all significant, as $p < 0{,}05$ (all of them being $p < 0{,}001$ or n/a). This provided evidence for the individual indicator's reliability (Cheung et al., 2024). As for internal consistency reliability, this was also confirmed as all of the constructs' Cronbach alpha and construct reliability were greater than 0,7. As a result, the predicted parameters for these relationships are not affected by measurement errors (Cheung et al., 2024).

To test convergent validity, it was crucial to look at one extra validation. Firstly, and as verified before, all items loaded at a minimum value of $0{,}79 > 0{,}5$, and they were all significant within their respective constructs. They all also had CR (construct reliability) greater than 0,7. With this in mind, and as Table 3 shows, the average variance extracted (AVE) for all of the constructs was greater than 0,5, which proved convergent validity (Cheung et al., 2024).

With convergent validity established, the first condition for discriminant validity was complete (Bagozzi et al., 1982). Many recommendations exist on how to evaluate discriminant validity, but in this study, it was tested using two procedures, the Fornell and Larcker criterion and the heterotrait – monotrait ratio (HTMT) criterion (Cheung et al., 2024). The Fornell and Larcker criterion requires that for any two given constructs, the AVE's square root of one's shared experience with itself is greater than any other (Fornell & Larcker, 1981). This establishes discriminant validity, and can be seen in Table 3 (the numbers in a diagonal, in bold). As for the heterotrait – monotrait ratio (HTMT) criterion (Henseler et al., 2015), all ratios were bellow the value of 0.85, except for one, which was the value between Performance Expectancy and Perceived Usefulness, which exceeded the conventional threshold (0,88). This is not unexpected, as there is a big theoretical link between these two constructs. Despite this finding, the overall model maintains strong validity indicated by all of the remaining excellent HTMT values for the other constructs and the Fornell Larcker criterion. providing additional evidence of discrimination validity – Table 3 (above the diagonal numbers in bold).

Table 3 - PLS: Cronbach's alpha, Composite reliability, Average Experience Extracted, Correlations and discrimination validity checks

	Cronbach's alpha	Composite reliability (rho_c)	Average variance extracted (AVE)	1	2	3	4
CuteN (1)	0,880	0,918	0,737	**0,858**	0,042	0,211	0,248
CuteY (2)	0,954	0,967	0,879	0,042	**0,937**	0,539	0,604
PerceivedUseful (3)	0,922	0,950	0,864	0,211	0,539	**0,930**	0,886
PerformanceExp (4)	0,876	0,916	0,731	0,248	0,604	0,886	**0,855**

With collinearity verified, as almost all the VIF values in the inner model were below the value of 5 (except for 1, whose value, despite exceeding the typical threshold, did not reach critical levels to undermine the interpretation of the results, at 5,362) – Table 4 – we moved on to the structural model. This was analyzed through the sign, magnitude and significance of the structural path coefficients; the magnitude of R squared for both endogenous variables in the model, as a measure of it's accuracy; and lastly by Stone-Geisser's Q squared values as a measure of predictive relevance (Hair et al., 2017). R squared coefficients were both above 10% (Falk, 1992), with the two endogenous variables Interest in Service Robots in Touristic Experiences and Service Robot Acceptance at 53% and 60%, respectively. These variables are central to the study as they receive input from all other predictor variables. The value being above 50% for both shows us that the predictor variables have a strong explanatory power on the variance of the dependent variables. As for the Q squared values, they also indicated the predictive relevance of the model, as both variables were very much above 0 (0,517 and 0,592) - Table 5.

Table 4 - PLS: VIF values

	VIF
CuteN -> InterestServRobots1	1,093
CuteN -> SRA1	1,093
CuteY -> InterestServRobots1	1,672
CuteY -> SRA1	1,672
PerceivedHuman -> InterestServRobots1	1,332
PerceivedHuman -> SRA1	1,332
PerceivedUseful -> InterestServRobots1	4,863
PerceivedUseful -> SRA1	4,863
PerformanceExp -> InterestServRobots1	5,362
PerformanceExp -> SRA1	5,362

Table 5 - Q squared values

	Q^2predict
InterestServRobots1	0.517
SRA1	0.592

We can, therefore, conclude that both the variables and the model are of quality.

Moving on to the hypothesis, Table 6 shows us that Cuteness (for people who have not interacted with service robots) positively influences Interest in Service Robots in Touristic Experiences in a significant way (β = 0,210, p < 0,001). Contrarily, Cuteness (for people who have not interacted with service robots) does not significantly influence Service Robot Acceptance (β= 0,039, n.s.). As for people who have interacted with a service robot, Cuteness does not have either a significant effect on Interest in Service Robots in Touristic Experiences (β = - 0,038, n.s) or in the Service Robot Acceptance (β = 0,094, n.s). These results provide support for H1N. As for H2N, H1Y, H2Y, enumerated respectively above, these hypotheses are not supported.

As for Perceived Humanness, it neither has a significant effect on Interest in Service Robots in Touristic Experiences (β = 0,097, n.s) or Service Robot Acceptance (β = 0,004, n.s). This means that these hypotheses (H3 and H4) are not supported.

Perceived Usefulness has a significantly positive relation with Interest in Service Robots in Touristic Experiences (β = 0,292, p < 0,05) and Service Robot Acceptance (β = 0,335, p < 0,01). This provides support for H5 and H6.

At last, Performance Expectancy has a significantly positive relation with Interest in Service Robots in Touristic Experiences (β = 0,360, p < 0,01) and Service Robot Acceptance (β = 0,398, p < 0,01). This supports H7 and H8.

Table 6 - Structural Model Assessment

	Path coefficient	Standard errors	t statistics	p values
CuteN -> InterestServRobots1	0,210	0,051	4,128	0,000
CuteN -> SRA1	0,039	0,049	0,803	0,422
CuteY -> InterestServRobots1	-0,038	0,065	0,582	0,561
CuteY -> SRA1	0,094	0,057	1,644	0,100
PerceivedHuman -> InterestServRobots1	0,097	0,055	1,775	0,076
PerceivedHuman -> SRA1	0,004	0,056	0,063	0,950
PerceivedUseful -> InterestServRobots1	0,292	0,118	2,483	0,013
PerceivedUseful -> SRA1	0,335	0,109	3,085	0,002
PerformanceExp -> InterestServRobots1	0,360	0,126	2,855	0,004
PerformanceExp -> SRA1	0,398	0,129	3,079	0,002

In order to establish a sort of "ranking" of importance, and therefore establishing the most important areas of future improvement in organizations looking to go this route and have a good strategic plan, we conducted a IPMA analysis (Teeluckdharry et al., 2024).

Firstly, we had to make sure that both requirements for the application of IPMA were met. First off, all indicator coding has the same direction. In this case, the scale is the same for Cuteness, Perceived Humanness, Perceived Usefulness and Performance Expectancy, from 1 to 5, where 1 – Totally Disagree and 5 – Totally Agree. The scale was also the same in the sense of a low number representing a "negative" opinion and a higher number a positive one for Interest in Service Robots in Touristic Experiences (1- Not interested at all and 5 – Very interested) and Service Robot Acceptance (1- Very unlikely and 5 – Very likely). As for the other factor, the outer weights must not be negative, as this might represent collinearity (Hair et al., 2017). As we can see by looking at Table 7, this criterion is also met, as all values are positive. This analysis was made for both Interest in Service Robots in Touristic Experiences and Service Robot Acceptance.

Table 7 - IPMA: Outer Weights

	Outer weights
CuteN1 <- CuteN	0,343
CuteN2 <- CuteN	0,310
CuteN3 <- CuteN	0,275
CuteN4 <- CuteN	0,232
CuteY1 <- CuteY	0,254
CuteY2 <- CuteY	0,273
CuteY3 <- CuteY	0,270
CuteY4 <- CuteY	0,269
InterestServRobots1 <- InterestServRobots1	1,000
PerceivedHuman1 <- PerceivedHuman	1,000
PerceivedUseful1 <- PerceivedUseful	0,343
PerceivedUseful2 <- PerceivedUseful	0,358
PerceivedUseful3 <- PerceivedUseful	0,374
PerformanceExp1 <- PerformanceExp	0,314
PerformanceExp2 <- PerformanceExp	0,302
PerformanceExp3 <- PerformanceExp	0,281
PerformanceExp4 <- PerformanceExp	0,271
SRA1 <- SRA1	1,000

The importance-performance map in Table 8 shows both the importance and performance of the constructs on Interest in Service Robots in Touristic Experiences and Service Robot Acceptance, separately of course. It is possible to draw some conclusions:

Performance Expectancy has the highest impact on generating interest in Service Robots in Touristic Experiences, with a value of 0.360, the highest of all values. However, the performance score (42.601) indicates that there is room for improvement in how well this expectation is currently met. As for Perceived Usefulness, it is the second most important factor for driving Interest in Service Robots in Touristic Experiences. Its performance score is relatively low, indicating that users do not find robots as useful as they could be. The results show us these two constructs as the areas that require the most managerial attention (Teeluckdharry et al., 2024). Finally, when analyzing Cuteness' impact on Interest in Robots in Touristic Experiences, it is interesting to see similar performance numbers for individuals who have and who have not interacted with service robots (46.808 and 48.369, respectively) and, despite this, totally different numbers when it comes to importance. As for individuals who have not interacted with a service robot, it's Cuteness is one of the most important aspects, while for individuals who have, the importance of Cuteness is a negative value (-0,038), which means that the cuter individuals who have interacted with a service robot perceive the robot to be, the less interested they are in having it in their touristic experiences. This might suggest that once the interaction happens, they start to value it's other functionalities, such as performance and usefulness, and it is an interesting managerial takeaway (Teeluckdharry et al., 2024).

When looking at the importance and performance of the same constructs in relation to Service Robot Acceptance, Performance Expectancy is also the most critical factor. Improving users' perceptions of how well the robot meets their expectations in this aspect could significantly increase acceptance. Also similar to before, Perceived Usefulness is the second most important construct in Service Robot Acceptance (0,335), but it has a low performance (38,931), meaning that there is a great opportunity here for development. Finally, when it comes to Cuteness in relation to Service Robot Acceptance, it is possible to conclude that in this case, it does play a role, although of very low importance, for both people that have interacted with service robots and people who have not.

Table 8 - Importance-Performance Map for Interest in Service Robots in Touristic Experiences

	Interest in Having Service Robots in Touristic Experiences	
	Importance	Performance
Cuteness (Never Interacted with a Service Robot)	0,210	48,396
Cuteness (Have Interacted with a Service Robot)	-0,038	46,808
Perceived Humanness	0,097	37,158
Perceived Usefulness	0,292	38,931
Performance Expectancy	0,360	42,601
	Service Robot Acceptance	
	Importance	Performance
Cuteness (Never Interacted with a Service Robot)	0,039	48,396
Cuteness (Have Interacted with a Service Robot)	0,094	46,808
Perceived Humanness	0,004	37,158
Perceived Usefulness	0,335	38,931
Performance Expectancy	0,398	42,601

5. Discussion

5.1 The Role of Cuteness in Influencing Interest in Service Robots in Touristic Experiences and Acceptance of Service Robots Among Different User Groups

Results show that Cuteness (for people who have not interacted with a service robot), positively influences Interest in Service Robots in Touristic Experiences ($\beta = 0{,}210$, $p < 0{,}001$). However, within this user group, the influence of Cuteness on Service Robot Acceptance is non-significant. This indicates, in terms of managerial implications, that a service robot's cuteness could have a role in generating initial interest, in line with (Guo et al., 2024)'s study, but not lead to its acceptance, where other factors such as performance and usefulness seem to be more relevant.

This is further supported by the fact that, for people who have had the experience of interacting with a service robot, Cuteness plays a weaker role than initially expected following (Joshua Paul Dale et al., 2017) thoughts, as both hypotheses deriving from this variable were non-significant. Even more so, this weak relation between Cuteness (for people who have interacted with service robots) and Interest has a negative value when it comes to importance. Although there are not a lot of papers on negative values of importance in IPMA, we know that as the importance of a variable decreases, its effect on the outcome becomes adverse (Ringle & Sarstedt, 2016) and this could mean that it actually holds a contrary effect, meaning that the cuter the robot is, the less Interest in Service Robots in Touristic Experiences people who have already interacted with one have. This, once again, points to a shift, as people go from intrigued, to deciding if they value it in their travel experiences.

Therefore, this study advances on (Guo et al., 2024)'s findings, as it shows that Cuteness does influence in Interest in Having Service Robot's in Touristic Experiences, but only moved by initial curiosity and only for people who have not yet interacted with service robots.

This could all be linked to the novelty effect. Novelty is experiencing something unique regarding an individuals' usual experiences (Barto et al., 2013), and it is seen as a driver of behavior, with the potential to lead to high emotions and peak experiences (Duman & Mattila, 2005; Gutierrez-Zotes et al., 2015). It can be divided between two types of novelty: retrospection (thinking about past experiences) and prospection (thinking about future experiences) (Skavronskaya et al., 2020).

Related to this is the concept of novelty seeking, usually used to understand customer behavior and travel destinations, being a crucial factor in travel choices (Skavronskaya et al., 2020). When it comes to prospection novelty, dreams, desires, goals and intentions have been four significant themes, which once achieved, resulted in strong emotional responses, both of pleasure and unpleasurable (Skavronskaya et al., 2020). This could further explain the contrast of Interest in Having Service Robots in Touristic Experiences between people who have not yet interacted with one (and therefore may have that goal or desire) and people who have had interaction and perhaps didn't have a pleasurable experience.

5.2 Hedonic vs Functional Motivation in the Adoption of Service Robots in Touristic Experiences

All of the hypotheses that were related to the functional motivations were supported, meaning that these constructs had positive and significant effects on the dependent variables. This is in alignment with TAM (Davis, 1989), and further contributes to this model, showing another functional factor which leads to the acceptance of technology in performance expectancy. It also aligns with (Seo & Lee, 2021) and (Wong A. & Wong J., 2024), as perceived usefulness significantly and positively affects both Interest in Having Service Robots in Touristic Experiences and Acceptance of Service Robots, therefore contradicting (Park et al., 2021). Finally, it furthers (Chiang & Trimi, 2020)'s findings through a positive relation lens, as better performance expectancy leads to the acceptance of service robots. As for hedonic factors, the only one that had a positive and significant effect was Cuteness (for people who have not interacted with a service robot), as previously mentioned.

(Chiang & Trimi, 2020)'s study also concluded that empathy, a hedonic factor, was one of the most important factors, as we are in the early stages of adoption of service robots. However, contrary to these findings, both hedonic factors showed generally non-significant results in influencing either Interest in Having Service Robots in Touristic Experiences or Acceptance of Service Robots. Focusing on Perceived Humanness, as Cuteness has been discussed already in the previous topic, the results didn't support the SRAM's notion that social-emotional elements play a factor in the acceptance of service robots (Wirtz et al., 2018), as well as contradicted (Ku, 2024) and (Wong A. & Wong J., 2024)'s findings, where this construct would affect Service Robot Acceptance in two separate touristic areas of their study.

This could be because of many factors, such as cultural differences, age and personality of respondents. It could also indicate that individuals in our demographic sample, specifically in the tourism sector, prioritize how well a robot performs a certain task, which aligns, in turn, with (Davis, 1989) TAM.

Another reason could be that, as this is a relatively new topic, users are still in an early phase of adjusting to robotic services, focusing more on their practical implications rather than engaging with them emotionally, contrary to (Chiang & Trimi, 2020)'s interpretation that in this phase that was one of the most important factors.

5.3 The Influence of Perceived Usefulness and Performance Expectancy on Interest in Having Service Robots in Touristic Experiences vs. Acceptance of Service Robots

Lastly, within the two functional factors, and as we set out to understand to what extent perceived usefulness contributes to shaping users' interests in service robots compared to its impact on their acceptance, the IPMA analysis conducted on these constructs brings forward new findings.

Through this analysis, it is possible to understand that while both constructs had a significant and positive impact on both the dependent variables, Performance Expectancy had the highest impact on both Interest in Having Service Robots in Touristic Experiences (0.360) and the Acceptance of Service Robots (0,398). This means that users place a premium on expected performance capabilities, and puts this construct as one of the most important when it comes to the Acceptance of Service Robots.

Perceived Usefulness, while also significant and important, had a slightly weaker importance on the generation of interest. This suggests that, while both contribute to Service Robot Acceptance, Performance Expectancy, which going back to the definition is the consumer's belief that the adoption of service robots will increase the ability and competency of satisfying their needs (Y. Lee et al., 2021) seems to garner more interest. This makes sense with (Venkatesh et al., 2003)'s proposal of performance expectancy as a development/evolution of the TAM's (Davis, 1989) perceived usefulness variable, in his UTAUT model (Venkatesh et al., 2003), a more complete construct. Therefore, this study advances that it would make sense to use performance expectancy in models such as (Wirtz et al., 2018)'s SRAM and any future developments.

Overall, Perceived Usefulness/Performance Expectancy's biggest impact in terms of importance was in the acceptance of service robots, meaning that above garnering initial interest, these constructs are important towards the long-term acceptance of service robots in touristic experiences.

6. Conclusion

6.1 Theoretical Contributions

This study provides some theoretical contributions, enhancing literature on tourism marketing, consumer adoption of service robots in this field and further tests and developments on the main models related with the subject (TAM, SRAM and UTAUT) (Davis, 1989; Wirtz et al., 2018;Venkatesh et al., 2003).

While Davis, (1989)'s TAM has traditionally focused on perceived usefulness and perceived ease of use as predictors of technology acceptance, this research picks out the most relevant one and integrates it, alongside the other constructs, in a two-stage adoption process by the consumer: interest and acceptance. This distinction between initial interest and acceptance bridges a gap in literature about service robots, as it covers the emotion of interest, which in itself is not very studied, as well as provides a better understanding of which phase exactly these functional factors have the most impact, seeing as there are also (although not yet definitely established) initial hedonic motivations (cuteness for people who have not yet interacted with a service robot). This study shows us that when transitioning to a later stage of adoption (acceptance), people seem to indulge in more functional considerations.

By adapting Wirtz et al., (2018)'s SRAM to a touristic context, this study contributes to the growing literature on service robots in the various touristic fields. By studying two constructs from each of the main factors in SRAM we contradict, for this sample and this demographic, the notion that social-emotional elements has an impact on the acceptance of service robots. A new variable is also introduced into the model, and it was in fact the only one that had a significant result regarding these social-emotional elements, which is cuteness, proving it to be one of the most fundamental influencers of human behavior (Steinnes et al., 2019) and studying this construct in different consumer groups, which there is not a lot if any literature about regarding service robots. As for the functional factors, the integration of Performance Expectancy led to the discussion that further studies should use this construct as a development of perceived usefulness, as proposed by (Venkatesh et al., 2003), having more significant results both in garnering initial interest and on the overall acceptance of service robots then perceived usefulness.

6.2 Managerial Implications

The findings of this study also offer several practical insights for tourism managers, businesses and marketing professionals considering the integration of service robots into their operations.

By understanding the factors that drive interest and acceptance of service robots, managers can align their strategies in a better way, enhancing customer experiences and operational efficiency.

The study shows that cuteness (for people who haven't interacted with service robots and perceived usefulness/performance expectancy are the drivers of interest, but only perceived usefulness/performance expectancy leads to a long-term acceptance. Managers can use this knowledge in robot design, focusing mainly on the functional factors of the robot, but still keeping a level of cuteness that is enough to attract interest from people who have not yet interacted with a service robot. For example, marketing professionals who work in digital marketing campaigns can create target audiences, impacting only people that they know have not interacted with their service robot, therefore taking advantage of its cuteness in this aspect. This can be a factor in drawing in visitors to their touristic related services. Managers have, therefore, an option on how to communicate, being able to even create customized communications strategies for different stages of consumer adoption.

However, and as mentioned before, when we move from client acquisition to client retention, functional factors are the only ones that play a role. In other words, it's all about the robot's performance and how the clients perceive its practical use. Therefore, managers should focus on the practical advantages of robots, ensuring that tourists see a continued value in their interactions with these technologies beyond the initial novelty phase.

In sum, managers should consider a phased approach to service robot deployment, starting with pilots that gather feedback from customers. This will allow them to better the functionality aspects and ensure long-term value is being delivered to these customers.

6.3 Limitations and Future Research

Even though we were able to extract valuable information from this study, it was not without its limitations.

First, data was collected at a single point in time, in a specific cultural context. The only mean of data collection was a questionnaire, and we had a relatively small sample size (187 completed answers). Future studies could use additional means of data collection, and maybe even apply this study to different cultural backgrounds, as cultural attitudes vary significantly, which can heavily influence results. Future studies could also have a wider window when it comes to data collection, which could even help validate the notion of initial interest and acceptance of service robots as two stages of the consumer funnel. The sample characteristics such as their age, gender a level of previous interaction with service robots were also a limiting factor, as we had a somewhat homogeneous sample when it comes to these factors. Future research could have a more heterogeneous sample, or even focus on a age, gender or previous interaction with service robots as a moderative variable.

Second, this study centered on key variables chosen due to relevance found in literature review: cuteness, perceived humanness, perceived usefulness and performance expectancy. While these were the factors that we found to be critical, there could be other factors that have as much if not more influence on interest in having service robots in touristic experiences and service robot acceptance. Future research could focus on understanding these factors, especially for interest, which there is a lack of literature on.

Further, future research could also focus on the negative result found in importance on the IPMA test for cuteness (for people who have interacted with service robots), as there was barely any literature on this type of result, while also investigating deeper into the motives behind the switch from having interest in interacting with service robots in touristic experiences for people who have not interacted with one, to it being a deteriorate.

As the service robot field is still in a somewhat embryotic state, we trust that these findings can be a foundation for further studies and help managers, companies and marketing decisions in the future.

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