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Are the Portuguese ready for the **future of tourism**? A **Technology Acceptance Model** application for the use of **robots in tourism**

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Abstract | The tourism sector has been growing exponentially in Portugal over the last few years, becoming increasingly competitive. On the other hand, the use of machines, robots and artificial intelligence in this industry that is built by and for people, has also been increasing and diversifying. The objective of this investigation focuses on the study of variables that can affect the acceptance of robots by the Portuguese public. The Technology Acceptance Model (TAM) is applied to understand the influence of a set of sociodemographic variables, travel behavior, motivation, and attitude towards technology in general in the perceived ease of use and perceived usefulness of using robots in tourism. The results obtained demonstrate that the Portuguese case is similar to that of other Western countries, with gender, age, travel group, motivation and attitude towards technology having a significant impact on the dependent variables.

Keywords | Robots, tourism, technology acceptance model, artificial intelligence

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1. Introduction

The tourism industry has gained great importance in Portugal over the last few years. The country won several "World Leading Destination" awards and the number of visitors grew exponentially, as well as the number of Portuguese travellers (INE, 2020a). In 2019 the residents accounted for 26.1 million overnight stays, a growth of 6% compared to 2018 (INE, 2020a). "Leisure, recreation or holidays" is the main motivation for travelling to Portugal (49.4%) (INE, 2020a).

At the same time, the explosion of the 'Fourth Industrial Revolution', or the 'Industry 4.0' has shown how technology is leaving the factories and entering everyday reality. Robots, Artificial Intelligence and Service Automation (RAISA) are rapidly developing and there are already several examples on our daily lives. Amazon's Alexa, Connie the Hilton's concierge, Aloft Hotels' Botlr, or the 'Spyce' restaurant are some examples of how long technology has come.

According to Bowen and Whalen (2017), one of the trends in the tourism sector is the increasing use of Artificial Intelligence (AI) to substitute humans. Considering the tourism sector is facing new challenges related to human-to-human interaction, it is of uttermost importance to understand what variables may affect robot acceptance and adoption so that stakeholders take the best possible advantage of these intelligent machines (Beer et al., 2011). Several models have been developed over the years to study technology acceptance, such as the Technology Acceptance Model (Davis, 1986), Unified Theory of Acceptance and Use of Technology Model (Ventakesh et al., 2003) and the Chain Model (Beer et al., 2011; Oliveira, 2015). These models can give extremely valuable information to developers, by providing information on the variables that influence user acceptance.

The goal of this research is to apply one of these models to the Portuguese context, in order to know if sociodemographic characteristics, tourism practices, the acceptance of technology in general and the motivation toward technology play a role in RAISA acceptance. This paper is divided in five sections, including a literature review, methodology explanation, data analysis and main conclusions.

2. Literature review

The importance of the tourism industry in the global economy is undeniable. It is responsible for one in every ten jobs globally, accounts for over 10% of the global DGP, creates demand and induces consumption and fosters development (WTTC, 2019). Tourism allows millions of families to gain an income, supporting mainly the minorities like women, young people and rural communities (WTTC, 2015; Aynalem, Birhanu & Tesefay, 2016). Also, tourism contributes to a fairer world, by creating more jobs and helping to reduce poverty and by promoting peace and understanding between cultures and people. It can a great ally in fulfilling the UN 17 Sustainable Development Goals. However, the travel and tourism industry is immensely affected by global tragic events, whether it is an economic crisis, an epidemic or a terrorist attack (Papatheodorou, Rosselló & Xiao, 2010). This kind of events may cause severe losses for tourism and for the economy itself, cause jobs to be lost, a decrease in the GDP, a reduction in international arrivals and many other constraints. People need to feel safe to travel and uncertainty causes stress and creates doubts.

The OECD (2018) has identified several trends that will impact the next decades and that everyone should be aware of. These trends were divided in four categories, regarding their key areas: people, planet, productivity, and polity (OCDE, 2018). The travel and tourism sector will be affected by these trends, and it is necessary for the industry to start preparing and planning. Out of

all of the trends that are rapidly emerging in the tourism sector, technology should be policy makers main focus, as it is the one with the potential to change the industry the most, either by creating or eliminating jobs, providing completely different experiences such as virtual reality or autonomous vehicles, or simply because of its contribute to an increasing sense of globalization where comparing prices or learning about consumer behaviour is quite simple (Neuhofer, Buhalis & Ladkin, 2013; Buhalis & Costa, 2006).

Automation has been a part of society since the creation of small mechanisms in Ancient Egypt (Stone, 2005). The industrial revolutions and wars, particularly, World War II, brough rapid advances, allowing for an exponential development of mechanisms and technology in a few years. These discoveries were applied in several fields, showing their importance in making human life easier at work and in daily activities (Satchell, 1998). Some of the main advantages of automation include higher production rates, increased productivity, more efficient use of materials, improved worker safety and better-quality products.

Table 1 | Main landmarks in the rise of automation

Year	Event
4 million ago	Tools/instruments appeared (Ramapithecus)
c. 1760	Industrial Revolution (UK)
1796	Watt: Modern factory (UK)
1800	Jacquard: Jacquard loom (France)
1818	Blanchard: Mechanical copying machine (USA)
1860	Principle of assembly line (USA)
c. 1873	Spencer: Automatic screw machine (USA)
1913	Ford: Conveyor-driven, flow-type car assembly (USA)
1930	Patent of numerical control (USA)
1947	Harder: Detroit (mechanical) automation (Ford Motor Co., USA)
1947	Remote manipulator (USA)
1950-60	Process automation (USA)
1952	Parsons: Three-axis NC milling machine (MIT, USA)
1954	Devol: Patent of industrial robot (USA)
1958	Automatic programming system - APT (USA)
1959	Polar-coordinate robot (Unimation Co., USA)
c.1965	Low-cost automation (Pennsylvania State University, USA)
1966	Automatic programming - EXAPT (Germany)
1991	Intelligent manufacturing system (IMS) project (JapanRISAI
2003	First controllers with embedded web server
2015	Henn-na hotel opens: One of the first hotels to have robotic staff
2018	First application of automated vehicles in the oilsands industry.

Source: Own construction, based on Hitomi (1994)

The Industry 4.0 represents a new way of producing and living. Benefiting from the ongoing advances in technology, cyber-physical systems allow interactions between the cyber world and the real world, creating a never-before-seen stage of connectivity and interaction (Schätz, et al., 2015; Özdemir, 2018). The technological advances brought by the Internet of Things (IoT) and Artificial Intelligence (AI) enable this extreme connectivity status and are closely connected to the arise of Smart Cities and Smart Factories that will improve production processes (Arasteh et al. (2016).

The IoT and AI are being used in the travel and tourism industry, even though it is still in early stages (Nadkarni et al., 2020). Technology is

mainly used in tourism to improve customer experiences rather than to simplify or enhance processes. However, the abilities of IoT and AI should be closely monitored by hotels and other travel and tourism agents, so that the sector may remain competitive, as it can also help to save money on energy costs and maintenance. Nevertheless, user's attitude toward technology is not always favourable (Tussyadiah & Park, 2017). Demographic and cultural variables are the most cited as predictors for technology acceptance, even though their role is not consensual (Cruz-Cárdenas et al., 2019; Ivanov et al., 2018). Several models were developed to try and understand technology adoption, so that the companies' investment in technology is not in vain (Taherdoost, 2018).

The use of robots has been growing exponentially in industry, services, and everyday life. A robot is a machine, programmable by a computer, that can carry out actions autonomously or semi-autonomously (ISO, 2012; Bartneck & Forlizzi, 2004). There are three main types of robots - robots that operate autonomously, robots that interact with other robots and robots that interact with humans – and these may have several forms. Studies show that the more a robot looks like a human the more humans expect it to act like one, leading to disappointment when it does not correspond (Tung & Au, 2018). On the other hand, human feature like smiling and head tilting may improve the customers perception regarding safety and reliability (Wirtz et al., 2018). Considering the different types of robots that exist, service robots are the most relevant for this study. Service robots are robots that interact, communicate, and provide services to a customer (Wirtz et al., 2018). Their use has been growing particularly in fields like medicine, caring for elders, and fighting viruses (Yang et al., 2020; Rantanen et al., 2018; Crișan, Andraș & Coman, 2017; Stollnberger et al., 2014). However, their use is not consensual among researchers (Ivanov, 2017), that can be roughly divided in two groups: one that believes robots may free men from dull and heavy work and another that fears humanity may became obsolete. The main advantages of robots over humans are their ability to work 24/7, the fact that they do not feel fatigue, do not get bored and do not complain about doing the same chores over and over (Ivanov & Webster, 2018; Wirtz et al., 2018). The disadvantages have to do with their lack of creativity and empathy (Ivanov, 2017).

Robots are also taking over the tourism industry, with many practical examples from robotic concierges to fully staffed robotic hotels. Labour shortages, language and cultural barriers and cost-effectiveness are the main reasons why the hospitality industry is choosing robots over people (Ivanov & Webster, 2018). The interaction with RAISA influences the tourist experience, thus the correct linkage between the phase of the guest cycle the tourist is in and the robot used is fundamental for a successful experience (Lukanova & Ilieva, 2019). Considering this interaction and the increasing regularity with which it happens, human-robot interaction studies are growing, and authors found some key attributes social robots should have. Besides, sociodemographic characteristics, past experiences and the type of robot and the way it looks may also influence customer's willingness to use service robots (Ivanov, Webster & Garenko, 2018; Ivanov, Webster & Seyyedi, 2018; Tung & Law, 2017; Nomura et al., 2006).

3. Methodology

The knowledge of whether the public will accept or reject a new information system poses a great challenge in the study of new technology, as it can be the crucial factor determining the success or failure of a project (Laumer & Eckhardt, 2011; Park, Lee & Cheong, 2007; Davis, 1993; Davis, Bagozzi & Warshaw, 1989). The Technology Acceptance Model (TAM), developed by Fred Davis

in 1986 (Figure 1), is a theoretical model that aims to explain how users come to accept technology and how they use that technology. To fulfil the purpose of this investigation, it was used to measure the acceptance of robots in tourism and to see to what extent can the defined external variables, the perceived usefulness (PU) and the perceived ease of use (PEOU), influence the acceptance of robots in tourism.

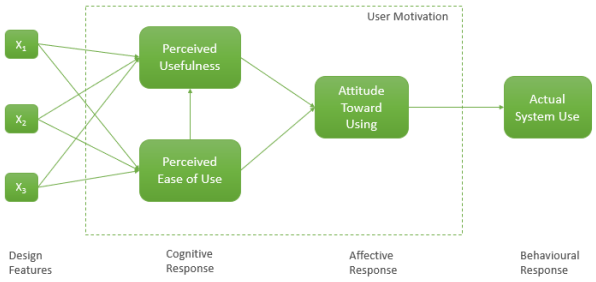

Figure 1 | Technology Acceptance Model
Source: Davis, 1986

To implement this model, four groups of external variables/design features were considered:

- Sociodemographic variables were established by Tung and Law (2017), Ivanov, Webster and Garenko, (2018) and Ivanov, Webster and Seyyedi (2018) as predictors of new technology/robots' acceptance.
- Travel characteristics, such as travel frequency, companionship, motivation and type of accommodation were also established as possible predictors of robots' acceptance in tourism (Xu, Li & Lu, 2019).
- Motivation to use technology is stated by Park et al. (2007) as one of the most relevant variables in its success. Also, instrumental use of technology with greater motivation produces stronger attitudinal and behavioural effects.
- The attitude toward technology in general was also considered, as Blut et al. (2016) believe that consumers highly technology ready are more likely to try technology and are thought to have less problems exploring it and less difficulties using it.

Considering the attitude toward technology feature, the Technology Readiness Index 2.0 scale was used. The item pools used for the attitude toward technology in general, used by Cruz-Cárdenas et al. (2019) were adapted by the original TRI 2.0 scale developed by Parasuraman and Colby (2014).

As far as the authors knowledge goes, TAM has only been applied to the Portuguese context once and the study regarded User Generated Content (Freitas & Santos, 2017). Hence, due to the lack of information regarding the factors that influence the acceptance of robots by Portuguese residents, this is an exploratory study. To collect quantitative primary data, a survey by questionnaire was developed and applied, based on the original TAM. Data was collected between November and December 2020, and given the target population of the questionnaire, the final version was developed in Portuguese using the Google Forms tool. Due to the current pandemic situation and in order to have a better spatial distribution of the respondents through Portugal, the link to the questionnaire was disclosed online.

The original TAM integrates four key categories: perceived ease of use, perceived usefulness,

attitude toward using, and actual use. As the number of people who have interacted with robots is diminished, the "attitude toward using" and the "actual use" features were not considered in this research, hence the study only contemplates the design features and cognitive response phases.

Hence, the four defined design features were measured as follows. The item Motivation towards technology was measured using a 1 to 4 Likert-type scale, with 1 meaning "Not important" and 5 meaning "Extremely important". Considering attitude toward technology, 13 items were used to measure respondents' attitude, with a Likert-type scale from 1- Strongly disagree to 5 – Strongly agree. Focusing on the PEOU dimension, respondents were asked to score each of the items on a scale from 1 – Strongly disagree to 5 – Strongly agree. Subsequent to the assessment of the PEOU and following the TAM, participants were asked to evaluate the item regarding Perceived Usefulness of robots in tourism, using a Likert type scale from 1- Never to 5 Always.

Considering the focus of this study, it was defined as target population every resident in Portugal not younger than 18 years old. As the final version of the questionnaire was in Portuguese, the lack of knowledge of the language was an excluding factor. Also, the questionnaire considered the respondent had travelled at least one time over the last three years. There was a total of 404 answers to the questionnaire. However, 14 respondents did not meet the criteria to be included in the target population, as 13 of them did not live in Portugal and one was 17 years old, so 390 responses were considered as valid in the data analysis.

The SPSS software was used to analyse the collected data, as it allows for the development of univariate, bivariate and multivariate analysis, needed to fulfil the investigation's goal. Besides the descriptive statistics, and to test the established hypotheses, two different types of analysis were conducted: i) bivariate analysis to compare differences between groups (t test and correlations) and ii) a multivariate regression to test cause-and-effect relationships between the independent and dependent variables.

To test the Internal Consistency reliability of the model, Cronbach's alpha was calculated. The survey items were all validated by the respective authors, nevertheless it is important to confirm their reliability for this specific context. Cronbach's alpha is based on the average correlation among the items studied (Bhatnagar, Kim & Many, 2014). Values over 0.7 mean the items used to measure that construct represents it correctly and generate similar scores. Table 2 shows the values of Cronbach's Alpha for each construct.

Table 2 | Cronbach's alpha

	Nº of items	Cronbach's Alpha
Motivation toward technology	4	0.840
Attitude toward technology	13	0.743
Perceived Ease of Use	9	0.685
Perceived usefulness	10	0.940

Source: Own construction

4. Results and discussion

4.1. Characteristics of respondents

Regarding the sociodemographic characterization of the sample, 67.7% of the respondents are female and 32.3% are male, 75.4% of the sample has superior education and 57.1% of the respondents are in the groups 635€- 999€and 1000€-1499€per month, which is in accordance with the monthly average income of 2018, 1166,9€(INE, 2020b). The sample has a good distribution among the age groups, but groups 25-29 (17.7%) and 45-49 (14.4%) stand out as the ones with higher percentages. The youngest respondent was 18 years old and the oldest 81 years old. Table 3 presents the sociodemographic profile of the respondents.

Table 3 | Sociodemographic profile

		Frequency	Percentage
Gender	Female	264	67.3
	Male	126	32.3
Education	Basic education	10	2.6
	Higher education	85	21.7
	Superior education	295	75.4
	Others	1	.3
Income	< 635€	43	11.0
	635€-999€	116	29.7
	1000€-1499€	107	27.4
	1500€-1999€	43	11.0
	≥ 2000€	38	9.7
	No income	44	11.3
Age	18-24	62	15.9
	25-29	69	17.7
	30-34	29	7.4
	35-39	35	9.0
	40-44	41	10.5
	45-49	56	14.4
	50-54	50	12.8
	55-59	28	7.2
	60-64	12	3.1
	+65 years old	8	2.1

Source: Own construction

In terms of geographical distribution, the district with the highest number of respondents was the district of Aveiro, with 102 people, followed by the district of Castelo Branco (82), Lisbon (64) and Porto (46). The district of Bragança was the only districts from where there were no respondents.

Travel behaviour was then analysed. Considering the number of trips over the last three years, respondents were scattered among the five categories, with 1 to 4 trips being the one with the highest percentage (35.9%), closely followed by 5 to 8 trips (32.6%). It is important to remember that 2020 was a very atypical year for travelling and travellers, as travelling was discouraged, and travel bans were applied.

Table 4 | Travel behaviour

		Frequency	Percentage
Number of trips last 3 years	1 to 4	140	35.9
	5 to 8	127	32.6
	9 to 12	61	15.6
	13 to 16	19	4.9
	Over 19	43	11.0
Travel group	Friends	51	13.1
	Partner	115	29.5
	Family	171	43.8
	Alone	31	7.9
	Business partners	20	5.1
	Other	2	0.6
Motivation	Leisure	285	73.1
	Business	37	9.5
	Health and well being	15	3.8
	Visiting family and friends	52	13.3
	Other	1	0.3
Organization	Independent	346	88.7
	Organized	44	11.3

Source: Own construction

Most of the respondents travel with their family (43.8%) or partner (29.5%) and the most referred travel motivation was leisure (73.1%) followed by visiting family and friends (13.3%). In what concerns travel organization, 88.7% of the respondents organize their trips themselves. Table 4 shows the travel behaviour of the respondents.

When asked about the duration of their trip, almost half of the respondents indicated that their travels usually last 3 to 5 days (46.9%), followed by those who answered 1 week (30.8). The accommodation categories were established based on the Portuguese terminology and law. Almost half of the respondents affirm they use mostly hotels (46.2%), followed by family or friend's house (19%).

Given the increasing use of robots in tourism and to assess if previous interaction with robots in this context could influence the respondents' perceived ease of use and perceived usefulness of robots in tourism, respondents were asked to state whether they have been hosted in as accommodation that uses robots. The response was quite expressive, as 351 participants (90%) have never had contact with robots in accommodation, and only 39 (10%) did.

The respondents who have had contact with robots were asked to state what kind of robots they had been in contact with. The most mentioned types of robots were self-check-in robots (25 respondents) and concierge robots (7 respondents).

4.2. Analysis of the items used in estimating TAM

As mentioned earlier, four constructs were used to estimate the model: i) Motivation toward technology, ii) Attitude toward technology, iii) Perceived ease of use and iv) Perceived usefulness. The model assumes several independent variables (Motivation toward technology, attitude toward technology) to estimate its dependent variables (Per-

ceived ease of use and Perceived usefulness). An analysis of the results of each item is here presented.

Starting with "Motivation towards technology", every item scored a mean slightly above 3, with the item "Save time using technology" scoring the highest value (3.31) and the item "Help other to use technology" scoring the lowest value (3.16).

Considering attitude toward technology, most respondents believed "technology improves quality of life" (M=4.05), "makes personal life more productive" (M=3.77) and "provides more control over it" (M=3.45). A large number of respondents also believe "people are too dependent on technology" (M=4.02) and that "too much technology distracts people" (M=3.79) and "lowers the quality of relationships" (M=3.81). In general, participants "keep up with the technological developments of interest areas" (M=3.39) and "can figure out new technological products and services without help" (M=3.06) but are not the "first to acquire new technology when it appears" (M=2.59). Most participants "do not have difficulties with support lines" (M=2.85) and they also "do not believe technology is not designed for ordinary people" (M=2.66). Besides, most respondents are "comfortable doing business online" (M=2.75).

Focusing on the PEOU dimension, respondents perceive the "use of automatic machines as easy to use" (M=3.44) and consider it "easy to remember how to execute task on these machines" (M=3.51). Accordingly, most of the respondents are "not confused by automatic machines" (M=2.78), "do not make frequent mistakes while using them" (M=2.53), "do not consider the interaction as frustrating" (M=2.36) or as "requiring of great mental effort" (M=2.37), "do not think machines behave unexpectedly" (M=2.45), "do not find them complicated to use" (M=2.46) and find it "easy to get a machine to do what they want" (M=3.23).

The results for the PU variable were all positive, with the lowest scored item being "Automatic machines support critical aspects of my trips" (M=3.29), and the highest "Technology gives me more control over my trips" (M=3.78), closely followed by "Using automatic machines improves the quality of my trips" (M=3.73). Respondents believe "automatic machines are useful in their trips" (M=3.55), stating they "make it easier" (M=3.46), "improve the quality of the trips" (M=3.34), "save time" (M=3.65) and "improve the travellers performance on the trip" (M=3.33), believing that "travel without technology would be hard" (3.38).

4.3. Hypotheses validation

To test the established hypotheses, two different types of analysis were conducted: i) bivariate analysis to compare differences between groups and ii) a multivariate regression to test cause-and-effect relationships between the independent and dependent variables.

The sociodemographic variables were recategorized as binary variables and, to test their relationship with the PEOU, the t of student test was performed. Equal variances were only assumed for gender and, looking at the test result, this is also the only group where the test result is lower than α (0.024), which means there are statistically significant differences between the groups. Hence, we fail to reject the null hypothesis and infer females have a better perceived ease of use of robots in tourism. For district and education level, the test result is greater than 0.05 (0.637 and 0.301, respectively), so we fail to reject the null hypotheses, meaning having a higher education degree or coming from a more developed area does not contribute to a more positive PEOU.

Table 5 | t of Student Test for gender, district and education (PEOU)

		N	Mean	Levene's test (sig.)	t-Test (Sig. 2-tailed)
Gender	Female	264	2.832	.200	.024
	Male	126	2.706		
District	Undeveloped	150	2.808	.009	.637
	Developed	240	2.781		
Education	No higher education	95	2.849	.003	.301
	Higher education	295	2.772		

Source: Own construction

Age and income were categorised as ordinal variables, hence their relationship with the PEOU was tested with Pearson's correlations. Test results show there is no relation between age and PEOU, and income and PEOU, as in both case the results is higher than the 0.05. Therefore, we fail to reject the null hypotheses and conclude that these two variables do not have a direct impact on the PEOU of robots in tourism.

Considering the travel group, motivation to travel, trip organization and accommodation were also recoded in binary variables and the t of student test was used to compare the groups regarding the PEOU. Equal variances were assumed for travel group, trip organization and accommodation. In all four variables the test result is greater than α, meaning we fail to reject the null hypotheses and infer travelling with family and friends, travelling in leisure, travelling independently and preferring hotels does not influence the PEOU (Table 6).

Table 6 | t of Student Test for travel behaviour variables (PEOU)

		N	Mean	Levene's test	Sig. (2-tailed)
Group	Others	52	2.776	.992	.813
	Family and friends	338	2.793		
Motivation	Other	105	2.858	.011	.168
	Leisure	285	2.767		
Organization	Independent	346	2.797	.414	.572
	Organized	44	2.750		
Accommodation	Other	157	2.844	.363	.101
	Hotel/Hostel	233	2.756		

Source: Own construction

The "Motivation toward technology in general" and "attitude toward technology" variables were both interval variables, hence the relation between these independent variables and the PEOU was tested using Spearman Correlations. Analysing the correlation coefficient, it is possible to determine that motivation toward technology in general influences the PEOU ($.012 \leq 0.05$). The correlation is positive but not very significant (-.127). Considering the attitude toward technology, the p-value is greater than 0.05 (0.063), meaning there is no correlation, thus we fail to reject the null hypothesis.

To further test the hypotheses, a multivariate regression analysis was conducted for the PEOU. The considered independent variables were gender, age, place of residence, education, income, usual travel group, motivation, organization and accommodation, motivation toward technology and attitude toward technology. The regression used the Enter method and is presented in table 7.

The results show the correlation coefficient $R^2 = 0.065$ and the adjusted $R^2=0.038$, meaning around 4% of the dependent variable variation is explained by the independent variables. Also, the Durbin-Watson test result (1.789) indicates that the residuals are not correlated. The multicollinearity tests show there is no significant correlation

Table 7 | Multivariate regression model (PEOU)

Independent variables	Unstandardized Coefficients		Standardized coefficients	t	p-value
	B	Std. Error	Beta		
Constant	2.599	.229		11.351	.000
Age	.008	.011	.039	.730	.466
Gender	-.150	.057	-.136	-2.650	.008
District	.001	.055	.001	.027	.978
Education	-.017	.067	-.014	-.256	.798
Income	-.021	.018	-.060	-1.167	.244
Travel group	.021	.088	.014	.232	.816
Travel motivation	-.098	.053	-.103	-1.849	.065
Accommodation	-.071	.057	-.068	-1.247	.213
Trip organization	-.058	.085	-.036	-.683	.495
Motivation toward technology	-.038	.069	-.033	-.548	.584
Attitude toward technology	.198	.055	.204	3.621	.000
Model summary					
R	.255				
R Square	.065				
Adjusted R Square	.038				
Std. Error of the estimate	.50589				
F-statistic	.007				
Multicollinearity					
Tolerance	>0.69				
VIF	<1.4				

Source: Own construction

between the independent variables, hence, no multicollinearity. With every assumption of the multivariate regression verified, the t-test result may be analysed. The regression analysis shows a statistically significant model, demonstrating that gender ($B = -.136$; $t = -2.650$; $p<0.05$) and attitude toward technology ($B = .204$; $t = 3.621$; $p<0.05$) are predictors of the PEOU. The linear equation should be as follows:

$$PEOU = 2.599 - .150(Gender) + .198(Attitude\ toward\ technology) + \epsilon$$

The second dependent variable was then tested, following the same principles. Starting with the sociodemographic variables, equal variances were assumed for district and education level. Considering the test results, statistically significant differences between the groups were found in the district variable ($p \leq 0.05$), meaning the null hypothesis was rejected and assuming that living in a more developed area contributes to the PU of robots in tourism. For gender and education, we failed to reject the null hypotheses, meaning they do not influence the perceived usefulness of robots in tourism. Equal variances were also assumed for district and education level. Considering the test results, statistically significant differences between the groups are found in the district variable ($p \leq 0.05$), meaning null hypothesis was rejected and it is assumed that living in a more developed area contributes to the PU of robots in tourism. For gender and education, we fail to reject the null hypotheses, meaning they do not influence the perceived usefulness of robots in tourism.

Table 8 | t of Student Test for gender, district and education (PU)

		N	Mean	Levene's test	Sig. (2-tailed)
Gender	Female	264	3.527	.005	.525
	Male	126	3.467		
District	Undeveloped	150	3.313	.130	.000
	Developed	240	3.629		
Education	No higher education	95	3.428	.919	.276
	Higher education	295	3.533		

Source: Own construction

Spearman's correlations were again used to analyse the relationship between age and income and the PU. Results showed no relation between income and PU, as p $\geq$ 0.05 (0.401), consequently the null hypothesis was rejected, and authors conclude income does not influence PU. Considering age, the p-value (0.033) shows that there is an association between the independent variable and the PU. The correlation is negative and very weak, as the coefficient is below 0.2 (0.043). Hence, the null hypothesis is rejected, and it is assumed that age influences the PU.

As for the travel behaviour variables, equal variances were assumed to travel motivation, organization, and accommodation. Travel group is the only variable with p $\leq$ 0.05 (0.007), thus the null hypothesis is rejected, and it is assumed travelling with family and friends contributes to the PU of robots in tourism.

Table 9 | t of Student Test for travel behaviour variables (PU)

		N	Mean	Levene's test	Sig. (2-tailed)
Group	Others	52	3.740	.027	.007
	Family and friends	338	3.471		
Motivation	Other	105	3.568	.755	.372
	Leisure	285	3.485		
Organization	Independent	346	3.495	.399	.420
	Organized	44	3.600		
Accommodation	Other	157	3.424	.223	.094
	Hotel/Hostel	233	3.564		

Source: Own construction

Spearman's correlations were once again used to test the Motivation toward technology in general and attitude toward technology in general relation with the PU of robots in tourism. Besides, the relation between the PEOU and the PU was tested using the same method. The test result indicates that there is an association between each of these three variables (0.000, 0.000 and 0.017 respectively) and the PU, thus the null hypothesis is rejected. Regarding the motivation and attitude toward technology, the correlations are positive and weak as both values are between 0.2 and 0.4. This means the better the motivation (0.303) and attitude (0.245) toward technology is the better the PU is. The PEOU is also correlated to the PU, however the correlation is negative and weak (-0.121), meaning the higher the PEOU is the lower the PU.

A multivariate regression analysis was also conducted for the PU to determine the linear regression equation that reasonably describes the relationship between the independent variables (gender, age, place of residence, education, income, usual travel group, motivation, organization and accommodation, motivation toward technology, attitude toward technology and PEOU) and the dependent variable. The regression used the Enter method and is presented in Table 10.

The results show the correlation coefficient R2 = 0.194 and the adjusted R2=0.168, meaning the independent variables explain around 17% of the dependent variable variation. The Durbin-Watson test result (2.028) shows that the residuals are not correlated, and the multicollinearity tests indicate there is no significant correlation between the independent variables, hence, no multicollinearity. The regression analysis shows a statistically significant model, demonstrating that age (B = -.147; t = -2.949; p<0.05), district (B = .176; t = -2.949; p<0.05), travel group (B = -.112; t = -2.068; p<0.05), motivation toward technology (B = .227; t = 4.378; p<0.05) and attitude toward technology (B = .200; t = 3.751; p<0.05) are predictors of the PU. The linear equation should be as follows:

PU = 1.822 - .147(Age) + .293(District) - .267(Travel group) + .340(Motivation) + .304(Attitude) + ϵ

Table 10 | Multivariate regression analysis for PU

Independent variables	Unstandardized Coefficients		Standardized coefficients	t	p-value
	B	Std. Error	Beta		
Constant	1.822	.387		4.705	.000
Age	-.047	.016	-.147	-2.949	.003
Gender	-.141	.084	-.082	-1.691	.092
District	.293	.080	.176	-2.949	.003
Education	-.120	.098	-.064	-1.232	.219
Income	.007	.026	.013	.272	.786
Travel group	-.267	.129	-.112	-2.068	.039
Travel motivation	.011	.101	.006	.107	.915
Accommodation	.058	.084	.035	.697	.486
Trip organization	-.016	.125	-.006	-.127	.899
Motivation toward technology	.340	.078	.227	4.378	.000
Attitude toward technology	.304	.081	.200	3.751	.000
PEOU	-.033	.075	-.021	-.435	.664
Model summary					
R	.440				
R Square	.194				
Adjusted R Square	.168				
Std. Error of the estimate	.73881				
F-statistic	.900				
Multicollinearity					
Tolerance	>0.69				
VIF	<1.5				

Source: Own construction

4.4. Discussion

Data analysis allowed to conclude that women have a slightly more positive attitude towards the PEOU in the use of robots in tourism. Gender has been identified as a predictor in several studies, though in different ways. The result obtained in this study supports those of Ivanov, Webster and Seyyedi (2018), as opposed to Ivanov, Webster and Garenko (2018). Age, education, district of residence and income do not seem to influence the PEOU, contrary to what has been identified in other studies (Ivanov, Webster & Seyyedi, 2018; Ivanov, Webster & Garenko, 2018; Tung & Law, 2017). When analyzing the variables of the type of traveler (travel group, motivation, accommodation and organization), none of the null hypotheses was rejected. These results are opposed to those of Xu et al. (2019), who state that each type of traveler considers specific determinants of satisfaction/dissatisfaction. Considering the motivation towards technology in general, there was no evidence of a significant correlation between this variable and PEOU. In contrast, the results of Park et al. (2007) show that the motivation to use technology systems has a positive impact in the PEOU. The attitude of users towards technology in general proved to be correlated to the PEOU. Although the correlation is weak, these results are in line with the studies carried out by Cruz-Cárdenas et al. (2019) and Yang (2013).

When analyzing the results of the multivariate regression, it is possible to see that only gender and attitude towards technology figure in the equation. The percentage of variation that these two variables explain is very low (about 4%). However, as this study falls under the category of social sciences, this value is expected to be low given the difficulty of predicting human behaviour.

Considering the second dependent variable, the sociodemographic variables, and contradicting the PEOU results, age and area of residence influence the PU. In agreement with the findings of Ivanov, Webster and Seyyedi (2018), the younger participants showed a less positive attitude towards the PU of robots in tourism. Living in a more developed area also has a positive impact on the UP of robots in tourism, as mentioned by Ivanov, Webs-

ter and Garenko (2018). When observing the variables that characterize the type of traveler, the travel group has a positive influence on the PU, that is, traveling with family and friends contributes to a more positive PU in the use of robots in tourism. Although the variables are not exactly the same, these results are in line with the results of Xu et al. (2019) that state that different types of travelers consider specific determinants. User motivation towards technology and attitude towards technology have a positive correlation with PU, as pointed out in other studies (Cruz-Cárdenas et al., 2019; Yang, 2013; Park et al., 2007). PEOU was negatively correlated with PU, in contrast to the results of Yang (2013), Blut et al. (2016) and Lee, Lin and Shih (2018).

Analyzing the multivariate regression model, the equation that includes the area of residence, age, travel group, attitude towards technology and motivation towards technology explains 17% of the variation in the dependent variable. The results reinforce the idea of Cruz-Cárdenas et al. (2019) that PU is a key predictor in Western cultures.

5. Conclusions

The on-going advances in technology cause a new era to bloom: the industry 4.0. This represents a new way of thinking, producing and living, focusing more on the connection and interaction between people and things. The Internet of Things and Artificial Intelligence enabled de creation of Smart Cities, Smart Factories and even Super-smart Societies. These advances are also used in services, including in the tourism industry, where each day there are more examples of technological solutions. The implementation of technology for customers to use is only as good as its use, and sometimes consumers have negative attitudes toward technology. Investigators have tried to clarify what demographic and cultural variables affect this attitude, but the results are not clear. Nevertheless, predicting the use of new technology is extremely important for investors, hence several models for technology acceptance have been designed.

Robots are a part of AI that has been rapidly developing and used in several areas, both in industry, services and everyday life. From robotic arms to fully staffed robotic hotels, the chances to interact with robots while travelling are growing and not everyone is a fan. The costs associated with implementing robots are still considerably high but the labour shortages and cultural barriers, especially in developed countries and the unique opportunity to create a memorable experience are conducting the hospitality industry to invest more in robots. Studies in human-robot interaction are fundamental for both academics and managers, to learn what influences customer's willingness to use service robots and what features may robots have that can help in this process.

The results obtained in this study show women are slightly more positive regarding the perceived ease of use of robots in tourism than men. However, this assumption was not proven for the perceived usefulness as there were no statistically significant differences between the groups. Contrary to what other studies have proved, age, education level, area of residence and income did not influence the PEOU of the respondents. Though, for the PU, age and area of residence proved to be significant and were considered as predictors of the dependent variable. For the remaining variables (gender, income and education level), the study failed to reject the null hypotheses. Regarding the variables that were used to characterize the type of traveller, none was significant in predicting the PEOU of robots in tourism. Nevertheless, there were statistically significant differences between those travelling with family and friends and others (alone, business partners or others) regarding the perceived usefulness of robots in tourism.

User's attitude toward technology in general proved to be positively correlated with PEOU and PU, even though the correlation was weak in both cases. Nonetheless, user's motivation toward technology was only proven positively correlated to the perceived usefulness of robots in tourism. Contrary to what was initially expected the PEOU and the PU were negatively correlated, although the correlation coefficient was very low. These variables were expected to be positively correlated, according to what was found in other studies, as it was expected for people who perceive robots ease to use to also perceive their usefulness, but this was not the case.

The multivariate regression analyses showed that only gender and the attitude toward technology in general should be considered in the linear equation for the PEOU and district, age, travel group, attitude toward technology and motivation toward technology should be considered for the PU. These equations explain around 4% of the first dependent variable and around 17% of the second. The low value of these percentages is expected to be due to two factors: i) the model used and ii) the nature of the study. The Technology Acceptance Model is a general model, used to measure the acceptance of any new technology in any field, hence it is not specific for robots' acceptance, lacking important aspects such as the robots' appearance or the tasks it performs. On the other hand, the fact that this study falls under the scope of social sciences explains the low percentage of the variation explanation, as human behaviour is hard to predict.

Overall, the study helped explaining the importance of some variables in robots' acceptance, eliminating other that were not significant. The main limitation of this study is fact that it does not consider the attitude toward using and the actual use of robots. Only 10% of the respondents (39 participants) had had previous experiences with robots in hotels, making it impractical to study those two constructs of TAM accurately. Another limitation of the study in the fact that TAM was designed for the acceptance of new technology in general, thus is does not consider specific aspects of robots' acceptance, such as the robot's appearance, having human-like features, the tasks it performs or the jobs it replaces or creates. Further investigation should be done to clarify the importance of sociodemographic characteristics, travel behaviour, motivation towards technology and attitude toward technology in predicting PEOU and PU of robots in the tourism industry, in other countries.

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