Exploring the acceptance of social robots in Public Spaces: A user-centred approach conceptual model

Manuel Mirante Granate

Departamento de Engenharia e Gestão, Técnico Lisboa, Universidade de Lisboa, Portugal.

Abstract: Social robots are designed to work, cooperate and socially interact with humans, and are expected to become ubiquitous in our society. Notwithstanding, the mere presence of these systems does not increase people's acceptance and willingness to interact. Thus, it is necessary to perform user-centred studies that evaluate the factors that influence user acceptance of social robots, to understand the attitudes and perceptions potential users have towards social robots, better meeting their expectations and needs. This study aims to propose a social robot acceptance model in the context of public places, evaluating the factors that influence the adoption of social robots by potential users in these environments, pushing the field of social robotics forward and contributing with guidelines and implications to future developers.

Keywords: social robot acceptance model, user-centred product development, public spaces, PLS-SEM

1. Introduction

Research suggests that the increasing presence of social robots does not immediately raise its acceptance nor its engagement rate (Graaf & Ben Allouch, 2013; Kato et al., 2005), representing some the major problems for the success of social robotics (Graaf et al., 2016). Consequently, research in the field social robotics has been changing its focus from mobility issues to the challenges of Human-Robot Interaction (HRI) (Garcia et al., 2007).

When studying user acceptance of social robots, it is crucial to research the fundamental motives why future users choose to adopt social robots, *i.e.* what are their perceptions, attitudes and intentions towards these robots (Graaf et al., 2016). Therefore, it is paramount to perform user-centred studies, that integrates the user at an early stage of the development process, to adapt its final design to the "needs" and "wants" of users.

2. Literature Review

2.1. Background

The new era of robotics, where mobility, sensory and vision capacity challenges have been mostly surpassed, is focused on Artificial Intelligence (Murphy, 2000). An era where robots are becoming autonomous and have social skills, *i.e.*, the ability to socially interact with each other, and most importantly with humans. Therefore, alongside AI, the fields of social sciences and social psychology also play a major role in the development of such social robotic systems, especially in the challenges inherent to human-robot social interaction.

The market of robotics has never been growing as it is nowadays. Industrial robots are continuously growing at a stable pace, while in the service robotics market this growth is even more evident. Regarding social robots, professional service robots, especially Public Relations, presenting an increase of 133% in units sold in 2016, in comparison to the previous year. Also, the personal service robots for households and for entertainment presented increases around 20-25%.

2.2. Social Robot: definition & application fields

Social robots are robotic systems programmed in a way for humans to see them as social, presenting behaviours that induce social responses from humans. Therefore the social behaviours of robots are created in the human's brain (Graaf et al., 2016). In line with this, Graaf et al. (2016) proposed the following definition of social robots, which was the one considered the most appropriate: *"robots that elicit social responses from their human users because they follow the rules of behaviour expected by their human users".* The main application fields of these robots are Health Care and Therapy, Education, Domestic and Workplace and Public Spaces (Leite et al., 2013).

In the healthcare and therapy and in the education fields, the intended users are mostly children and the elderly with health problems. Also, the employment of social robots seems to have positive effects even with simpler robots in terms of technology and capabilities (Dorothée et al., 2009; Kramer et al., 2009). This might be due to the simplicity of tasks required for children's therapy and education and to the physical need from an elder for the robot to perform simple tasks. In addition to this, while user acceptance is still considered a challenge in some studies (Kanda et al., 2004) and a success in others (Kramer et al., 2009; Wada & Shibata, 2007), the perception of the existing social robots as social agents was mainly achieved, and long term engagement was found positive in most experiments.

In the workplace context, literature on long term evaluation of social robots is very scarce.

Gockley et al. (2005) is one of the closest to the workplace scenario, as interaction with users performed daily. In this study it is observed that after a certain amount of time, participants lost interest in the robot, verifying low levels of social robot acceptance on the long-term.

Furthermore, as the domestic application of robots requires daily, long term interactions and due to the fact that most existing social robots are still quite limited in terms of intelligence and capabilities (Graaf et al., 2017), the application of such systems at homes is not yet visible and studies often show low acceptance rates over time (Fernaeus et al., 2010; Graaf et al., 2014; von der Pütten et al., 2011). On the other hand, service robots that perform their tasks efficiently, such as Roomba, have been found to be a success (Forlizzi & DiSalvo, 2006).

In the public spaces, there is a shortage of literature. Research notices social robots present a high level of user acceptance (Kanda et al., 2010; Niemelä et al., 2017; Weiss et al., 2015). This might be explained by the frequently short period of time of the human-robot interactions in such environments which does not give users enough time to go beyond the novelty effect and notice the robot's limitations.

The acceptance of social robots by human seems to be higher when the interaction time between the robot and a user is lower. Thus, in public spaces, where interactions are, mostly, very short, and as long as tasks are achievable by the robot's capabilities, the acceptance rates are expected to be the highest for the existing robotic systems. In addition, the market of professional service robots for public relations (social robots in public spaces), presented the highest increase rate, presenting an increase of 133% in units sold in 2016, compared to 2015, and an astonishing expected growth for 2017-2020.

Thus, it is argued that the introduction of social robots in our society starts by employing social robots in Public Spaces. Thus, whilst technological evolution allows for social robots to become more sophisticated and affordable, the introduction of social robots in Public Spaces, might be the bridge that will enable potential users get used to the presence of such systems in today's society. In Portugal, as in 2018 Beltrão Coelho became the first distributor of social robots for rental, and as in 2019, the government employed the first ever social robot ,"Lola", in a Citizen's Bureau.

2.3. Social Robot Acceptance Models

Research shows, the most prominent models in technology acceptance are the TPB (Ajzen, 1985), the TAM (Davis, 1986) and the UTAUT (Venkatesh et al., 2003). All these models have been considered successful in predicting intention to use. Also, all these models have been successfully applied to predict technology acceptance and, used as a basis in social robot acceptance (Giger & Piçarra, 2018; Graaf et al., 2017; Heerink et al., 2010; Shin & Choo, 2011).

While the UTAUT was designed for employee acceptance of technology, Venkatesh et al., (2012) proposed an extension of the this model, the UTAUT2, for consumer acceptance of technology. This model is composed by seven determinants of use intention (UI): Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Hedonic Motivation (HM), Price and Habit; and three determinants of actual use: UI, FC and Habit.

Thus, mostly through social psychology models, the field of Information Systems (IS) has made substantial findings in the understanding and in the improvement of the human interaction with computer-based technologies (Kiesler & Hinds, 2004). Such social psychology models have found how intention can be a good determinant of behaviour, including acceptance behaviour.

Following the research fields of prior technology acceptance, the field of social robot acceptance, has presented several acceptance explorative studies, concept models and theories. For Socially Interactive Robots (SIR) in general (Shin & Choo, 2011) and in the contexts of Healthcare (Broadbent et al., 2009; Heerink et al., 2010; Klamer & Ben Allouch, 2010), Education (Fridin & Belokopytov, 2014), Domestic (Graaf & Ben Allouch, 2013; Graaf et al., 2017; Young et al., 2008) and Workplace (Giger & Piçarra, 2018).

Actual use is considered the best measure of social robot acceptance. The dimension UI has been found to be the main determinant of actual use and has been used as a measure for anticipated acceptance in short-term social robot acceptance studies (Fridin & Belokopytov, 2014; Giger & Piçarra, 2018; Graaf et al., 2017; Shin & Choo, 2011). In turn, Intention to Use is considered to be mainly determined by the variables Usefulness, Ease of Use, Adaptability, Enjoyment, Sociability and Social (Fridin & Belokopytov, 2014; Graaf & Ben Allouch, 2013; Graaf et al., 2017; Heerink et al., 2010; Shin & Choo, 2011). Most studies have performed HRI experiences with potential users (Heerink et al., 2010; Shin & Choo, 2011). Other resorted to video representation of robots (Giger & Piçarra, 2018). In both procedure participants then answered a questionnaire. Most models were tested with Structural Equation Modelling (SEM) (Giger & Piçarra, 2018; Graaf et al., 2017; Heerink et al., 2010; Shin & Choo, 2011).

Moreover, there is very scarce number of studies in the context of public spaces and it was not found any literature employing a conceptual acceptance model in the application field Public Spaces.

Thus, this study is focused on addressing to this research gap, by developing a social robot acceptance model in Public Places and testing it with a sample of the Portuguese population. Hence, contributing to the field of social robotics with a user-centred study, in a very promising context, the public spaces.

The basis that was chosen for the development of this model was the UTAUT2. The selection of this basis was due to fact that for the development of this model it was paramount to include the variables that were found the most influencing for the acceptance of social robots (*i.e.* usefulness, ease of use, adaptability, enjoyment, sociability and social presence). Thus, as the UTAUT2 includes most of the aforementioned variables, only lacking on sociability and social presence - variables specific to the essence of social robots.

3. Methodology

3.1. Conceptual Model for social robot acceptance in public spaces

This study proposes an extension of the UTAUT2 by adding two dimensions specific to social robots, *i.e.*, sociability and social presence.

The UTAUT2 assumes that behavioural intention determines usage behaviour which is, consequently, the outcome variable when evaluating the acceptance of technology in the short term. The model is composed by seven main components that directly influence behavioural intention - performance expectancy, effort expectancy, social influence, hedonic motivation, facilitating conditions, price and habit; and two that directly influences Use Behaviour: facilitating conditions and behavioural intention. Only one of the variables added by the authors (Venkatesh et al., 2012) was kept: Hedonic motivation, which has also been found to be a key construct for social robot acceptance (Graaf et al., 2017; Heerink et al., 2010). The other two dimensions price and habit were removed. Price, which is relevant for social robot acceptance (Graaf et al., 2017), though, not for the context of public spaces, as the users do not purchase them, instead, they are provided by organizations. Habit, which has only been considered influential in longitudinal studies of social robot acceptance (Graaf et al., 2014), being especially related to usage behaviour, thus, not possible to be measured in the present short-term study. The inclusion of sociability and social presence in the UTAUT2 attempts to provide an acceptance model specific for social robots, that assumes these variables as direct determinants of UI of such systems. Therefore, this model assumes the following hypotheses, as observed in Figure 1:

H1: The user's Performance Expectancy has a positive direct influence in their intention to use social robots in public spaces.
H2: The users' Effort Expectancy has a positive direct influence in their intention to use social robots in public spaces.
H3: The users' Social Norms has a positive direct influence in their intention to use social robots in public spaces.
H4: The users' Facilitating Conditions has a positive direct influence in their intention to use social robots in public spaces.
H5: The users' Hedonic Motivation has a positive direct influence in their intention to use social robots in public spaces.
H6: The user's Perceived Social Presence of social robots has a positive direct influence in their intention to use them in public spaces.
H7: The user's Perceived Sociability of these robots has a positive direct influence in their intention to use them in public spaces.

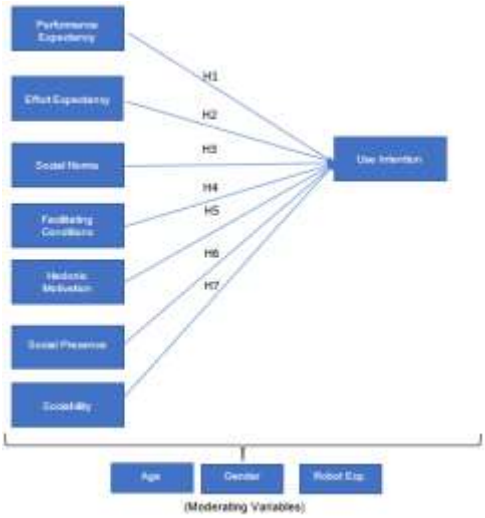

Figure 1: Proposed conceptual model for the acceptance of social robot in public spaces

All measures resorted to a 7-point Likert scale. The outcome variable, UI was measured with a scale from Graaf et al. (2017), which derived from Moon & Kim (2001). PE was measured with items from usefulness and adaptability. The measures used were withdrawn from Heerink et al. (2010), alongside with EE. HM was measured based on the enjoyment scale presented by Heerink et al. (2010). For SB and SP, the scales respective to these constructs presented by Heerink et al. (2010) were considered the most appropriate. SN was measured with items from social influence and status. For social influence, this was scale from Lee et al., (2006), whilst, for status, this was the version of the Image scale (Moore & Benbasat,

1991), presented by Venkatesh & Davis (2000). Finally for FC, the scale chosen to measure this construct was withdrawn from Giger & Piçarra (2018), an adaptation of the scale presented by Richetin & Perugini (2008). The items used to measure each dimension are displayed in Appendix A.

3.2. Data gathering procedure

A questionnaire was developed in Google Forms to test this model and evaluate the anticipated acceptance of social robots in public places. Due to the complexity of social robots, a definition, with emphasis on the context of public places, was selected to give the respondents the required knowledge to answer the questionnaire. Also, a video was developed using SonyVegas Pro, to integrate the questionnaire. This video compiles a few interactions of people with four social robots in public spaces.

The robots selected for this study (Figure 2) were considered the latest and most successfully employed nowadays, in the context of the present study. These robots are Spencer, Cruzr, Promobot and NAVii.

Figure 2: Social Robot used in the video. From left to right: Spencer, Promobot, NAVii and Cruzr.

The link to the questionnaire was sent by email, Facebook, and WhatsApp to family and friends. Each was asked to share this link with friends or family (snowball sampling). In addition, the questionnaire was posted on Facebook, in my personal profile, in the students' page of the Masters, in a non-official page of Instituto Superior Técnico, and shared by a few friends in their respective personal profiles. The entire form took approximately 10 minutes to fill and was on-line from the 30th of July to the 22nd of August, in order to obtain the desired number of responses, which was of 300 respondents, as it will be justified in the following chapter.

3.3. Data Analysis Strategy

A preliminary analysis of data was performed at first to scrutinize the sample and select only valid answers for the following analyses. In addition, it also highlights the descriptive statistics. After, the analysis is conducted using the PLS-SEM and is divided in two parts, the evaluation of the outer model and the evaluation of the inner model. Finally, a brief analysis of the robot preferences of the sample is performed, generally comparing the four robots used, and which were considered the favourite of the sample attempting to understand why.

The application of the PLS-SEM was chosen due to the explorative nature of this study alongside the expected non-normal distribution of data derived from Likert Scales. The methodology follows the guidelines given by Hair, Hult, Ringle, & Sarstedt (2017) - Figure 3. The software chosen to the SmartPLS 3.2.8, and some support was given by IBM SPSS 23.

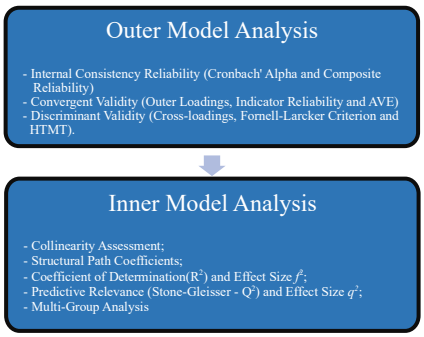

Figure 3: The PLS-SEM methodology, adapted from Hair et al. (2019)

4. Results

4.1. Preliminary Analysis

The questionnaire yielded a total of 305 responses. An examination of the answers was performed to exclude the answers of participants that did not showed enough commitment or effort (e.g. straight lining), 47 cases were identified, and the sample was reduced to 258 valid answers.

To detect multivariate outliers, the Mahalanobis was used. Three outliers were detected, with a result from the division of the value of the Mahalanobis Distance by the Degrees of freedom, higher than 3. Thus, the number of valid answers was reduced to 255.

There were identified only six missing values, which is under the 5% threshold given by Kline (2011). Thus, mean replacement was chosen as the substitution method (Hair et al., 2017).

The sample is composed by 53.7% males and 46.3% females. Most participants were in the age group 18-34 (67.8%). Most participants were either workers on the behalf of other (47.1%) or students (31.4%). In terms of education, most participants had either a Bachelor's (39.6%) or a Master's (37.6%) degree. Finally, 50.6% of the participants have never had experience with robots, while 49% have had.

The descriptive statistics indicated that the sample expresses the highest mean values (above 4.4) for the indicators associated with UI, PE, EE, FC, HM, for the SN indicators -SN01 and SN02, and for SB01. The indicators with the lowest mean values (below 3.4) are those associated with SP, three indicators from SB (SB02, SB03 and SB04) and two indicators associated with SN - SN03 and SN04. Values of skewness (sk) and kurtosis (ks) indicate that, for the recommended thresholds of $-1 < sk < 1$ and of $-1.5 < ks < 1.5$ (Schumacker & Lomax, 2004),

there are some items outside the this skewness threshold (FC02, FC03, SP01, SP02 and SP03) and one item outside the threshold for kurtosis (SP02). Thus, such results suggest, for these indicators, a non-normal distribution.

4.2. PLS-SEM Analysis

I. Outer model Analysis

To evaluate the internal consistency reliability both the Cronbach's Alpha and the Composite Reliability (CR) were inspected. Results for the Cronbach's Alpha of the original model show that all the constructs express values above the threshold of 0.70. On the other hand, when analysing the CR, it was verified that for the construct SN, internal consistency reliability was not achieved (0.692). Nonetheless, this value is close the threshold value of 0.70, and thus, was kept for further analysis.

To evaluate the convergent validity, the first step is to observe if the outer loadings of the indicators are above the threshold of 0.70. The second is to check if the AVE of every construct is above the 0.50, meaning that in average every indicator explains more than 50% of the variance of this construct. Although the threshold for the outer loadings is set at 0.70, for exploratory research, it is recommended that indicators with values below 0.60, should be dealt with, i.e. dropped, merged into another construct or creating another construct (Hair et al., 2017). When analysing the outer loadings, the construct SN, SN03 and SN04 present values below 0.40. Thus, these indicators were excluded as the remaining ones, SN01 and SN02, which measure "social Influence", better express the concept of the construct SN. Also, in the construct SB, one indicator (SB01) presented a very high loading, while the other three presented low values with two of them in (SB03 and SB04) with values below 0.60. The option was to remove SB01, which resolved the problem.

The other measure of convergent validity is the Average Variance Extracted (AVE), which is the average of how many of the variance of a Construct is explained by its indicators. Again, problems were only found in the same constructs as before, *i.e.*, SN and SB. Findings show a value lower than the threshold 0.50 for SN (0.40), and very close to this threshold (0.505) for SB. The alterations performed in the previous step (exclusion of SN03, SN04 and SB01), improved the values of the AVE in both of the problematic constructs above the threshold of 0.50.

Finally, to evaluate its discriminant validity, there are three criteria: the assessment of the cross-loadings, the Fornell-Larcker criterion and the HTMT, with the last one being the most reliable (Henseler et al., 2015).

At first one must check the cross-loadings of the indicators. According to this criterion, the values of the indicator's outer loadings must be higher than the values of the cross-loadings in the same row and line. It was verified that discriminant validity was achieved for all the constructs, except for PE and UI, presenting some values of the cross-loadings between indicators and constructs, higher than the outer loadings in the same row or line.

Turning to the Fornell-Larcker criterion, there is discriminant validity of the outer model when the values of the correlations between the constructs are lower than the square root of the AVE for that particular construct. The value of the correlation between SB and SP (0.748), is higher than the square root of the AVE of SB (0.717), though it is not higher than of the SP (0.869). Additionally, the correlation between UI and PE (0.928) was higher than both the square roots of the AVE of UI (0.825) and PE (0.798).

The results for the HTMT show discriminant validity for all the exogenous constructs, *i.e.*, all values of HTMT are below the thresholds of 0.90 (classic) and 0.85 (conservative), though, this was not verified between PE and UI. Notwithstanding, discriminant validity was achieved between these constructs according to another criterion, that considers there is discriminant validity if the value one is not included in the confidence interval generated by the bootstrapping - the value for HTMT was 0.882 for the percentile 2.5% and 0.973 for the percentile 97.5%. Therefore, as the HTMT is considered the most reliable of the three criteria (Henseler et al., 2015), the model was assumed to have achieved discriminant validity.

II. Inner Model Analysis

All the changes previously performed were already considered. The first step in the analysis of the inner model is to inspect the model for collinearity, *i.e.*, check the VIF. The recommended threshold for PLS-SEM is 3. Results indicated a multicollinearity issue with the construct in the construct SB, with a VIF above 3. To deal with this, alternative models were tested, where SB was considered an antecedent of SB and HM, and finally a model without SB. As a result, the construct SB was excluded, as the alternative model showed no changes from the one with SB excluded. The major factors for this decision were the high correlations between SB and SP (0.748) and between SB and HM (0.628) and the fact that SB has been shown a determinant of both the other constructs (Heerink et al., 2010). Consequently, this alteration led to the structure of the final model (Figure 2), for which the values of the VIF

for every exogenous construct are below 3, as observed in Table 4.

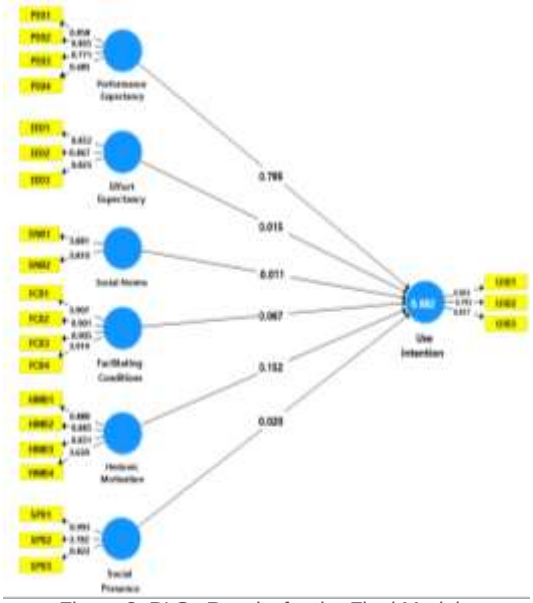

Figure 2: PLSc Results for the Final Model

For the final model, the results from the outer model analysis can be observed in tables 1, 2 and 3. All criterion for Internal consistency reliability, convergent and discriminant validity were above the threshold.

Table 1: Internal Consistency Reliability and AVE

	Cronbach's α	CR	AVE
EE	0.884	0.884	0.718
FC	0.950	0.950	0.825
HM	0.882	0.885	0.661
PE	0.870	0.875	0.637
SN	0.833	0.833	0.715
SP	0.901	0.902	0.755
UI	0.864	0.864	0.680

Table 2: Results of the Fornell-Larcker Criterion

	EE	FC	HM	PE	SN	SP	UI
EE	0.848						
FC	0.741	0.908					
HM	0.293	0.359	0.813				
PE	0.388	0.342	0.683	0.798			
SN	0.390	0.413	0.627	0.580	0.846		
SP	0.128	0.102	0.393	0.361	0.288	0.871	
UI	0.416	0.402	0.724	0.928	0.584	0.372	0.825

Table 3: Results from the HTMT Criterion

	EE	FC	HM	PE	SN	SP	UI
EE							
FC	0.741						
HM	0.292	0.356					
PE	0.390	0.341	0.687				
SN	0.389	0.413	0.632	0.588			
SP	0.125	0.102	0.390	0.369	0.289		
UI	0.416	0.402	0.728	0.930	0.584	0.374	

Table 4: Collinearity Statistics: VIF

	VIF
EE	2.374
FC	2.381
HM	2.361
PE	2.162
SN	1.890
SP	1.214

The results from the path coefficients reflect only two constructs with some relevance, i.e. PE and HM, as depicted in Table 5. PE has a path coefficient of 0.795 which is considered very relevant, and was also significant, at the significance level of $p<0.01$ (p-value of 0.000), thus supporting the first hypothesis (H1): "*The user's PE directly influences their intention to use social robots in public spaces.*" The path coefficient of the relation between HM and UI, representing hypothesis 5 (H5) has a value of 0.152 which is considered relevant and this value was significant at $p<0.05$ (p-value of 0.043), therefore, supporting the fifth hypothesis (H5): "*The user's HM directly influences their intention to use social robots in public spaces.*" All the other four hypotheses were not supported by the model evaluation, as not only their path coefficients were not relevant, they were also not significant.

Since the very high influence of PE on UI might affect influences of the other non-significant dimensions, it was decided to run a model without this dimension. Again, it was found that the only significant dimension was HM, although the dimensions EE, SN and social presence were found significant at $p<0.10$. Only the dimension FC was still not significant at all, suggesting that it might be a candidate to be excluded in future research.

Table 5: Path Coefficients

	β- value	Standard Deviation	t-value	p-value
EE -> UI	0.015	0.083	0.180	0.857
FC -> UI	0.067	0.079	0.839	0.401
HM->UI	0.152	0.075	2.024	0.043
PE -> UI	0.795	0.069	11.521	0.000
SN -> UI	-0.011	0.067	0.169	0.866
SP -> UI	0.020	0.052	0.382	0.703

The results from the PLS-SEM algorithm express that the six exogenous variables of the model explain about 88.2% of the variance of UI (R^2=0.882, p-value=0.000). According to Hair et al. (2017), values of R^2 above 0.67 are considered substantial. The effect size (f^2) of the exogenous constructs on the endogenous construct was assessed, revealing no effects from EE, FC, SB and SN. HM expressed a value of 0.063, which is above 0.02 and below 0.15, thus eliciting a weak positive effect. PE, on the other hand, expressed a very high value, way above, 0.350, thus presenting a strong positive effect on UI of Social robots in public spaces.

The predictive relevance (Q^2) and its respective effect size (q^2) were also assessed, using the blindfolding for the calculations. Hair et al. (2017) argues that a value of Q^2, above zero shows that proposed conceptual model has sufficient predictive. Findings revealed that UI has a Q^2 value of 0.532, indicating a strong predictive relevance. The effect size (q^2) in the predictive relevance was also computed. The thresholds are the same as for the effect size (f^2). While almost all the exogenous constructs indicate a lack of effect in the predictive relevance, the constructs PE and HM, express, respectively, a moderate (q^2= 0.34) and a weak

(q^2= 0.04) effect in the predictive relevance of the endogenous construct.

The results from the Multi-Group Analysis MGA), following Matthews (2017), using the permutation method indicate that none of these differences was found statistically significant (Table 6, 7 and 8), most likely due to the small samples size of the groups. However, results for the path coefficients suggest that for the age group 18-34, UI is mostly influenced by PE (β=0.607; p-value=0.000) and HM (β=0.242; p-value=0.000), while for the age group >34, the only significantly influencing variable is PE (β=0.738; p-value=0.000). Also, the values of the path coefficients indicate that for females, the relevant constructs that influence UI are PE (β=0.585; p-value=0.000) and HM (β=0.212; p-value= 0.008). For males, also PE (β=0.709; p-value=0.000) and HM (β=0.139; p-value=0.036) effect UI. Finally, for previous robot experiences, the path coefficient results reveal that for respondents without previous robot experience UI is mainly influenced by PE (β=0.597; p-value=0.000), HM (β=0.212; p-value=0.006) and SP, almost significant at 0.1 (β=0.101; p-value=0.110), while for respondents with previous robot experience the most influencing constructs of UI are PE (β=0.697; p-value=0.000), HM (β=0.165; p-value=0.006) and FC, at 0.1 significance level (β=0.124;p-value=0.080).

Table 6: Permutation results for the effect of age

	β (18-34)	β (>34)	β Dif.	2.5%	97.5%	p-Value
EE -> UI	0.057	-0.023	0.080	-0.24	0.270	0.555
FC -> UI	0.043	0.169	-0.126	-0.251	0.243	0.370
HM -> UI	0.242	0.099	0.142	-0.203	0.203	0.199
PE -> UI	0.607	0.738	-0.131	-0.193	0.201	0.212
SN -> UI	0.045	-0.041	0.086	-0.196	0.198	0.411
SP -> UI	0.037	0.000	0.036	-0.163	0.187	0.705

Table 7: Permutation results for the effect of gender

	β (F)	β (M)	β Dif.	2.5%	97.5%	p-Value
EE -> UI	0.034	0.023	0.012	-0.222	0.238	0.929
FC -> UI	0.105	0.035	0.070	-0.243	0.217	0.571
HM -> UI	0.212	0.139	0.073	-0.212	0.211	0.504
PE -> UI	0.585	0.709	-0.124	-0.185	0.180	0.189
SN -> UI	0.058	0.028	0.029	-0.179	0.177	0.733
SP -> UI	0.036	0.052	-0.016	-0.171	0.178	0.843

Table 8: Permutation results for the effect of robot experience

	β (No RRE)	β (RRE)	β Dif.	2.5%	97.5%	p-Value
EE -> UI	0.074	0.018	0.055	-0.227	0.241	0.629
FC -> UI	0.013	0.124	-0.11	-0.243	0.247	0.368
HM -> UI	0.212	0.165	0.047	-0.197	0.201	0.639
PE -> UI	0.597	0.697	-0.1	-0.186	0.179	0.266
SN -> UI	0.012	0.027	-0.015	-0.176	0.175	0.865
SP -> UI	0.101	-0.014	0.114	-0.163	0.165	0.181

4.3. Analysis of the Sample Preferences

Results show that the robot that was considered the most likable and attractive was Cruzr. In terms of sociability, Promobot surpassed Cruzr, though, by a very small margin. The mechanoid robot (Oshbot) presented the lowest mean values of the four robots in all the characteristics. Thus, results are in line with the "share of heart" question as the robot that was preferred by the largest amount of participants was Cruzr (34.2%), immediately followed by Promobot (28.8%), then Spencer (22.6%), with Oshbot as the least selected robot as a participants' favourite (14.4%). This suggests the anthropomorphic or humanoid appearance is preferred instead of a mechanical one.

4.4. Discussion and Implications

Considering the measurement model, results indicated that the construct SN cannot be measured with indicators from "social influence" and "image/status", dimensions that were proposed to be included in the construct SN. This is due to the fact that the indicators from "Social Influence" are weakly correlated with the indicators from "image/status", with values below 0.30. As such, if one wants to include the dimension "image/status" in a conceptual model, it should be measured separately from "social influence". A model with "Image" as a separate dimension was tested and compared to a model where this dimension was dropped. Since the results in common for the two models are very similar, the option was to keep only the dimension "social influence". Also, the item SB01, that referred to the pleasantness of the interaction with the robot, proposed in Heerink et al. (2010) was removed from the dimension SB. This was due to the low correlation between SB01 and the other indicators measuring SB. Alongside with this, it was verified that SB01 was more correlated with the indicators measuring the dimension HM.

Concerning the inner model, the dimension SB was excluded, due to collinearity issues with SP and, to a minor degree, with HM. In addition, a model was tested with SB as an antecedent of those two other variables (SP and HM). Results were in line with Heerink et al. (2010), confirming the influence of SB on both SP and HM. However, when comparing this model with a model with SB dropped, the results that are common to both models were not affected.

The PLS-SEM analysis yielded only two out of the six proposed variables of the final Extended UTAUT 2 model as significant predictors, *i.e.*, PE and HM. Notwithstanding, 88.2% of total variance explained in the endogenous construct, the intention of potential Portuguese users of using social robots in public spaces. This represents an unusually high value, though, the UTAUT was found to explain around 70% of the variance of UI (Williams, Rana, & Dwivedi, 2015), and other UTAUT2 studies have also achieved very high values of the R^2 (77%) for UI (Cimperman et al., 2016).

PE refers to the beneficial outcomes that using a social robot in the public spaces brings to a user, its utility or relative advantage. This variable has been shown to be the key critical construct of social robot acceptance in public spaces by a sample of potential Portuguese users, *i.e.*, the findings indicate that this construct is the most important determinant of the endogenous variable, UI, with a β=0.795 (p-value=0.000).

Therefore, H1: "*The user's Performance Expectancy has a positive direct influence in their intention to use social robots in public spaces*.", was empirically supported. Such high influence of PE on reported UI, have been witnessed in similar studies of social robot acceptance in other contexts (Heerink et al., 2010; Shin & Choo, 2011). Such high influence may be explained by the increasingly busier lives of modern society, where the use social robots in public spaces might reduce the time and effort of some actions. In addition, this confirms the influence of PE that has been noted in some studies, although with different methodologies and approaches, in the context of public places, such as social robot acceptance (Kanda, Shiomi, Miyashita, Ishiguro, & Hagita, 2009; Weiss et al., 2008, 2015), drone acceptance (Ramadan, Farah, & Mrad, 2016; Zhang, Liang, & Yue, 2015) and non-anthropomorphic robot acceptance (May et al., 2017). Therefore, results suggest that for social robots to be used in public spaces, the applicability of the robot must be clear and meaningful in a way that it is beneficial for the user. Thus, this reinforces Broadbent et al. (2009) and Graaf et al. (2017), as they suggested that the developers of such systems must guarantee the robot's purpose is clearly defined and that expectations are met, even if they had to be lowered.

HM is related to an individual's experience of using a social robot, and it is considered a pleasure-oriented variable with no clear functionality justification. In this study it refers to the user's perceived enjoyment of hypothetically using a social robot in public spaces. This was the only other dimension that was found relevant and significant as a determinant of UI with β=0.152 (p-value=0.043). Thus, empirically supporting H5: "*The users' Hedonic Motivation has a positive direct influence in their intention to use social robots in public spaces*." Such results are in line with Graaf & Ben Allouch (2013), Heerink et al. (2010), Shin & Choo (2011) and Graaf et al. (2017), revealing that potential users expect for the experience with the social robot would be enjoyable and pleasant. Also this supports the findings of studies in public spaces of social robot (Kanda et al., 2009; Weiss et al., 2008, 2015) and non-anthropomorphic robots (May et al., 2017; Ramadan et al., 2016), as they have also found that HM positively influences UI. Hence, developers must take this under consideration and try to understand which functionalities, appearance, stances, gaze and voices are the most likely to elicit HM in potential users.

The other four constructs (EE, SN, SP and FC) were not found relevant, nor significant, which led to the rejection of H2, H3, H4 and H6. Considering EE, similar results were found in Graaf et al. (2017). On the other hand, this goes against the findings of Heerink et al. (2010), which indicate that EE has a relevant and significant effect on UI. For SN, also similar findings were presented in Graaf et al. (2017), though, going against the findings of Shin & Choo (2011) and of Giger & Piçarra (2018), that conclude that SN has a relevant and significant positive effect on UI. In addition, the lack of relevance and significance on the effect SP has on UI was also encountered in Graaf et al. (2017), contradicting Heerink et al. (2010), that reports an indirect effect of SP in UI and Shin & Choo (2011), whose results indicate a strong positive and significant effect of SP in UI. Concerning FC, the findings in this study go against Heerink et al. (2010), Graaf et al. (2017) and Giger & Piçarra (2018), that have found FC to be relevant and significant. While one social robot study performed in the domestic context confirms the lack of relevance and significance of the effect of EE, SN and SP in UI, for FC there were no studies presenting similar results, what might indicate this phenomena is exclusive to the context of public spaces. This might be explained by the fact that for other contexts than the public spaces, the concept of FC includes other dimensions alongside the self-efficacy, for instance, affordability or availability. Thus, suggesting that FC might be a candidate to be excluded when evaluating the acceptance of social robots in public spaces. Also, it is possible that, with larger sample all the effects of these dimensions would be significant. Additional future research could be done to confirm the low relevance of these dimensions.

In addition, the broad comparison of the four robots suggests that developers should consider the anthropomorphic or humanoid appearance to be the one to be applied to social robots (with special attention when developing humanoid, not entering the uncanny valley), instead of a mechanical appearance.

5. Conclusions, Limitations and Future Work

5.1. Main Conclusions

Results from the model analysis indicate that the dimension UI was strongly predicted, with major influences of PE, *i.e.*, the usefulness of the robots, and of HM, *i.e.*, the fun-related experience associated with the interaction with the robot. This suggests that for social robots to be successfully developed for, and employed in public spaces, developers must take under consideration that the robot must be and use-oriented and fun.

The results of this study, are in line with the findings in the literature review, indicating a

high UI by potential users. This high acceptance rate may be explained by the short interaction time inherent to the context of public spaces, where the use of the robot is only for a practical and useful purpose. This way, developers could take advantage of the novelty effect and of the fact that the public spaces provides conditions for mass usage, to gradually integrate social robots in society, making users and potential users get used to these robotic systems.

To conclude, in order to develop acceptable social robots, it is paramount to consider potential users and their inputs, in order to meet their expectations. This study contributes to the understanding of users' anticipated acceptance of social robots in public spaces by proposing an extended model of the UTAUT2 and evaluating the dimensions that influence the intention to use these systems.

5.2. Limitations and Future Work

Due to time and cost constraints, it was not possible to conduct a real-life experience between potential users and a social robot, which is considered to increase the acceptance of this systems (Niemelä et al., 2017). Thus, a definition of social robot was given in the questionnaire to the participants, along with a video that was developed. Notwithstanding, future research could focus on conducting a similar study that includes a real-life experience with a social robot in a public scenario. In addition, this study does not evaluate the "actual" acceptance of social robots by potential users, on the long-term. Therefore, the actual use of social robots could not be measured. Hence, future studies are encouraged to develop long-term studies of social robot acceptance in public spaces, measuring actual use.

Additionally, this study was only performed with a sample of the Portuguese population, and thus, the evaluation of cross-cultural differences could not be performed. As such, future research is encouraged to replicate this study across many countries, to investigate how the nationality and culture may influence the acceptance of social robots in public spaces.

Furthermore, it is encouraged for future research to replicate the present study with the CB-SEM, to compare the results, possibly confirming the model.

Also, the conceptual model proposed in this study could be adapted and replicated in other contexts of social robot application, such as domestic, healthcare and therapy and education.

The MGA revealed that none of the differences observed between the compared groups were found statistically significant, what might be a consequence of the small sample size of the groups. Therefore, future research must address this issue and evaluate these moderating effects with an appropriately larger sample.

Further, future studies are recommended to conduct a more in-depth analysis on social robot preferences of potential users, alongside an analysis of the most appropriate and desired public spaces for potential users, where social robots should be employed. This way, enabling developers to be more informed in the conception of the robot's functions, and thus, being able to reach the expectations and the needs of users, consequently increasing their acceptance.

6. References

Ajzen, I. (1985). From Intentions to Actions: A Theory of Planned Behavior. *Action Control*.

Broadbent, E., Stafford, R., & MacDonald, B. (2009). Acceptance of healthcare robots for the older population: Review and future directions. *International Journal of Social Robotics*.

Cimperman, M., Makovec Brenčič, M., & Trkman, P. (2016). Analyzing older users' home telehealth services acceptance behavior-applying an Extended UTAUT model. *International Journal of Medical Informatics*.

Davis, F. D. (1986). A technology acceptance model for empirically testing new end-user information systems: theory and results.

Dorothée, F., Powell, S., & Dautenhahn, K. (2009). A long-term study of children with autism playing with a robotic pet: Taking inspirations from non-directive play therapy to encourage children's proactivity and initiative-taking. *Interaction Studies*.

Fernaeus, Y., Håkansson, M., Jacobsson, M., & Ljungblad, S. (2010). How do you play with a robotic toy animal? *Proceedings of the 9th International Conference on Interaction Design and Children*.

Forlizzi, J., & DiSalvo, C. (2006). Service robots in the domestic environment. *Proceeding of the 1st ACM SIGCHI/SIGART Conference on Human-Robot Interaction*.

Fridin, M., & Belokopytov, M. (2014). Acceptance of socially assistive humanoid robot by preschool and elementary school teachers. *Computers in Human Behavior*.

Garcia, E., Jimenez, M. A., De Santos, P. G., & Armada, M. (2007). The evolution of robotics research. *IEEE Robotics and Automation Magazine*.

Giger, J., & Piçarra, N. (2018). Predicting intention to work with social robots at anticipation stage: Assessing the role of behavioral desire and anticipated emotions. *Computers in Human Behavior*.

Gockley, R., Bruce, A., Forlizzi, J., Michalowski, M., Mundell, A., Rosenthal, S., … Wang, J. (2005). Designing robots for long-term social interaction. *2005 IEEE/RSJ International Conference on Intelligent Robots and Systems*.

Graaf, M. M. A. de, Allouch, S. Ben, & Dijk, J. A. G. M. Van. (2016). Long-Term Acceptance of Social Robots in Domestic Environments : In- sights from a User ' s Perspective. *AAAI Spring Symposium on Enabling Computing Research in Socially Intelligent Human-Robot Interaction*.

Graaf, M. M. A. de, & Ben Allouch, S. (2013). Exploring influencing variables for the acceptance of social robots. *Robotics and Autonomous Systems*.

Graaf, M. M. A. de, Ben Allouch, S., & van Dijk, J. A. G. M. (2014). Long-term evaluation of a social robot in real homes. *Interaction Studies*.

Graaf, M. M. A. de, Ben Allouch, S., & van Dijk, J. A. G. M. (2017). Why Would I Use This in My Home? A Model of Domestic Social Robot Acceptance. *Human-Computer Interaction*.

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2017). *A Primer on Partial Least Squares Structural*

Equation Modeling (Second).
Heerink, M., Kröse, B., Evers, V., & Wielinga, B. (2010). Assessing acceptance of assistive social agent technology by older adults: The almere model. *International Journal of Social Robotics*.
Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*.
Kanda, T., Hirano, T., Eaton, D., & Ishiguro, H. (2004). Interactive Robots as Social Partners and Peer Tutors for Children: A Field Trial. *Human – Computer Interaction*.
Kanda, T., Shiomi, M., Miyashita, Z., Ishiguro, H., & Hagita, N. (2009). An affective guide robot in a shopping mall. In *in HRI'09 4th ACM/IEEE International Conference on Human-Robot Interaction*.
Kanda, T., Shiomi, M., Miyashita, Z., Ishiguro, H., & Hagita, N. (2010). A communication robot in a shopping mall. *IEEE Transactions on Robotics*.
Kato, K., Bartneck, C., Nomura, T., Kanda, T., & Suzuki, T. (2005). A cross-cultural study on attitudes towards robots. *HCII '05: Proceedings of the 11th International Conference on Human-Computer Interaction*.
Kiesler, S., & Hinds, P. (2004). Introduction to This Special Issue on Human-Robot Interaction. *Human – Computer Interaction*.
Klamer, T., & Ben Allouch, S. (2010). Acceptance and use of a social robot by elderly users in a domestic environment. *Proceedings - 2018 11th International Conference on Human System Interaction*.
Kline, R. (2011). *Principles and Practice of Structural Equation Modeling*. The Guilford Press.
Kramer, S. C., Friedmann, E., & Bernstein, P. L. (2009). Comparison of the effect of human interaction, animal-assisted therapy, and AIBO-assisted therapy on long-term care residents with dementia. *Anthrozoos:A Multidisciplinary Journal of the Interactions of People and Animals*.
Lee, K. M., Jung, Y., Kim, J., & Kim, S. R. (2006). Are physically embodied social agents better than disembodied social agents? : the effects of physical embodiment, tactile interaction, and people's loneliness in human–robot interaction. *International Journal of Human- Computer Studies*.
Leite, I., Martinho, C., & Paiva, A. (2013). Social Robots for Long-Term Interaction: A Survey. *International Journal of Social Robotics*.
Matthews, L. (2017). Applying Multigroup Analysis in PLS-SEM: A Step-by-Step Process. In *Partial Least Squares Path Modeling: Basic Concepts, Methodological Issues and Applications*.
May, D. C., Holler, K. J., Bethel, C. L., Strawderman, L., Carruth, D. W., & Usher, J. M. (2017). Survey of Factors for the Prediction of Human Comfort with a Non-anthropomorphic Robot in Public Spaces. *International Journal of Social Robotics*.
Moon, J., & Kim, Y. (2001). Extending the TAM for a World-Wide-Web context. *Information & Management*.
Moore, G. C., & Benbasat, I. (1991). Development of an Instrument to Measure the Perceptions of Adopting an Information Technology Innovation. *Information Systems Research*.
Murphy, R. (2000). *Introduction to AI Robotics*. The MIT Press Cambridge.
Niemelä, M., Arvola, A., & Aaltonen, I. (2017). Monitoring the Acceptance of a Social Service Robot in a Shopping Mall: First Results. *HRI '17 Proceedings of the Companion of the 2017 ACM/IEEE International Conference on Human-Robot Interaction*.
Ramadan, Z. B., Farah, M. F., & Mrad, M. (2016). Technology Analysis & Strategic Management An adapted TPB approach to consumers ' acceptance of service-delivery drones. *Technology Analysis & Strategic Management*.
Richetin, J., & Perugini, M. (2008). Theoretical Models of Behavioral Predictions and Post-Behavior Evaluations. *Psychology & Marketing*.
Schumacker, R., & Lomax, R. (2004). *A beginner's guide to structural equation modeling. London: Lawrence Erlbaum Associates*.
Shin, D.-H., & Choo, H. (2011). Modeling the acceptance of socially interactive robotics: Social presence in human–robot interaction. *Interaction Studies*.
Venkatesh, V., & Davis. (2000). A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies. *Management Science*.
Venkatesh, Viswanath, Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User Acceptance of Information Technology: Toward a Unified View. *MIS Quarterly*.
Venkatesh, Viswanath, Thong, J. Y. L. T., & Xu, X. (2012). Consumer Acceptance and Use of Information Technology: Extending the Unified theory of Acceptance and Use of Technology. *MIS Quarterly*.
von der Pütten, A. M., Krämer, N. C., & Eimler, S. C. (2011). Living with a robot companion. *Proceedings of the 13th International Conference on Multimodal Interfaces*.
Wada, K., & Shibata, T. (2007). Living with seal robots - Its sociopsychological and physiological influences on the elderly at a care house. *IEEE Transactions on Robotics*.
Weiss, A., Bernhaupt, R., Wollherr, D., Kühnlenz, K., Tscheligi, M., & Buss, M. (2008). A Methodological Variation for Acceptance Evaluation of Human- Robot Interaction in Public Places. *Proceedings of the 17th IEEE International Symposium on Robot and Human Interactive Communication*.
Weiss, A., Mirnig, N., Bruckenberger, U., Strasser, E., & Tscheligi, M. (2015). The Interactive Urban Robot : User-centered development and final field trial of a direction requesting robot. *Paladyn Journal of Behavioral Robotics*..
Williams, M. D., Rana, N. P., & Dwivedi, Y. K. (2015). *The unified theory of acceptance and use of technology (UTAUT): A literature review*. *Journal of Enterprise Information Management*.
Young, J. E., Hawkins, R., Sharlin, E., & Igarashi, T. (2008). Toward acceptable domestic robots: Applying insights from social psychology. *International Journal of Social Robotics*.
Zhang, G., Liang, H., & Yue, Y. (2015). An investigation of the use of robots in public spaces. In *The 5th Annual IEEE International Conference on Cyber Technology in Automation, Control and Intelligent Systems*.

Appendix A: Items from the measurement model

Item	Source
UI01: Assuming I have the opportunity to use these robots, I would use them on a regular basis in the future.	Moon & Kim (2001);
UI02: I'm willing to put an effort to use these robots.	Giger & Piçarra (2018);
UI03: I will strongly recommend others to use these robots.	Moon & Kim (2001);
PE01: I think these robots are useful to me.	Heerink et al. (2010)
PE02: It would be convenient for me to have these robots at my disposal.	
PE03: I think these robots can be adaptive to what I need.	Heerink et al. (2010)
PE04: I think these robots help me accomplish things more quickly.	Venkatesh et al. (2012)
EE01: I think I will know quickly how to use these robots.	Heerink et al. (2010)
EE02: I find these robots easy to use.	
EE03: I think I could use these robots without any help.	
SN01: People will find it interesting to use these robots.	Lee, et al. (2006)
SN02: People will find these robots attractive.	
SN03: People who use these robots have more prestige than those who do not.	Venkatesh & Davis (2000)
SN04: People who use these robots have a higher profile than those who do not.	
FC01: I would be able to use these robots.	Giger & Piçarra (2018)
FC02: I'm confident that I have the knowledge to be able to use these robots.	
FC03: I can interact with these robots.	Richetin & Perugini (2008)
FC04: I can communicate with these robots.	
HM01: I would enjoy interacting with these robots.	Heerink et al. (2010)
HM02: I find these robots enjoyable.	
HM03: I find these robots fascinating.	
HM04 (R): I find these robots boring.	
SP01: I can imagine these robots as living beings.	Heerink et al. (2010)
SP02: Sometimes I think these robots are real people.	
SP03: Sometimes these robots seem to have real feelings.	
SB01: I think these robots would be pleasant to interact with.	Heerink et al. (2010)
SB02: I feel that these robots would be able to understand me.	
SB03: I consider that these robots would be pleasant conversational partners.	
SB04 : I think these robots are nice.	