Exploring the acceptance of social robots in Public Spaces:

A user-centred approach Model

Manuel Mirante Granate

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Supervisors: Prof. Carlos Manuel Ferreira Monteiro
Prof. Carlos Baptista Cardeira

Examination Committee

Chairperson: Prof. Miguel Simões Torres Preto
Supervisor: Prof. Carlos Manuel Ferreira Monteiro
Member of Committee: Prof. João Agostinho de Oliveira Soares

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Abstract

Over the last years, the technological progresses achieved in Artificial Intelligence (AI) and in other technologies such as sensors, batteries, processors, cloud-based systems and the Internet of Things (IoT), have given the field of robotics the necessary tools to develop and deploy social robots. 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 public places. The proposed model is an extended version of the UTAUT2 and was tested using PLS-SEM. Results showed that the main determinants of the intention to use social robots in public spaces are performance expectancy and hedonic motivation, meaning the usefulness of the robot and the fun-related experience directly affect the acceptance of these systems in public spaces. Also, the moderating effects of age, gender and experience were evaluated with Multi-Group Analysis and no statistically significant differences between path coefficients were found.

This way, by understanding the factors that influence the acceptance of social robots by potential users, in these environments, this study pushes the field of social robotics forward and contributes with guidelines and implications to future developers.

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

Resumo

Ao longo dos últimos anos, os progressos alcançados em Inteligência Artificial (AI), sensores, processadores, sistemas de cloud e Internet of things (IoT), levaram ao desenvolvimento e implementação de robôs sociais. Estes robôs são desenvolvidos para trabalhar, cooperar e interagir socialmente com seres humanos. É esperado que estes se tornem omnipresentes na nossa sociedade; não obstante, a mera presença destes sistemas não aumenta a sua aceitação, nem a vontade de interagir com os mesmos. É por isso necessário realizar estudos centrados no utilizador que avaliem os fatores influenciadores da aceitação de robôs sociais, para entender as suas atitudes e perceções, de modo cumprir com expectativas e necessidades.

Este estudo propõe um modelo de aceitação de robôs sociais em espaços públicos. Este modelo é uma versão estendida do UTAUT2 e foi testado usando PLS-SEM. Os resultados mostraram que os principais determinantes da intenção de usar robôs sociais em espaços públicos são a expectativa de desempenho e a motivação hedónica, o que significa que a utilidade do robô e a diversão associada à interação afetam diretamente a aceitação destes sistemas em espaços públicos. Além disso, os efeitos moderadores da idade, sexo e experiência também foram avaliados com análise multi-grupo (Multi-Group Analysis) e não foram encontradas diferenças estatisticamente significativas entre os coeficientes de percurso (path coefficients).

Desta forma, ao entender os fatores que influenciam a aceitação destes robôs por potenciais utilizadores nestes ambientes, este estudo impulsiona o ramo da robótica social e contribui com diretrizes e implicações para o desenvolvimento de futuros robôs sociais.

Palavras-Chave: Modelo de aceitação de robôs sociais, desenvolvimento de produto centrado no utilizador, espaços públicos, PLS-SEM.

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List of Abbreviations

AI - Artificial Intelligence

ASD - Autistic Spectrum Disorder

AVE - Average Variance Extracted

BCa – Bias Corrected and Accelerated

C-TAM-TPB - Combined TAM and TPB

CB-SEM - Covariance Based Structural Equation Modelling

CoBots - Collaborative Robots

CORAL - Cooperate, Observe the World, Reason, Act and Learn

CR - Composite Reliability

EE - Effort Expectancy

FC - Facilitating Conditions

HCI - Human-Computer Interaction

HM - Hedonic Motivation

HRI - Human-Robot Interaction

HTMT - Heterotrait-Monotrait ratio

IDT - Innovation Diffusion Theory

IFR - International Federation of Robotics

IS - Information Systems

IoT - Internet of Things

MATH - Model of Acceptance of Technology in Households

MGA - Multi-Group Analysis

MGB - Model of Goal-Directed Behaviour

MICOM - Measurement invariance of composite models

MM - Motivational Model

MPCU - Model of PC Utilization

MuMMER - MultiModal Mall Entertainment Robot

PE - Performance Expectancy

PEOU - Perceived Ease of Use

PLSc - Consistent PLS Algorithm

PLS-SEM - Partial-Least Square Structural Equation Modelling

PU - Perceived Usefulness

SAR - Socially Assistive Robotics

SB - Sociability

SCT - Social Cognitive Theory

SEM - Structural Equation Modelling

SIR - Socially Interactive Robots

SP - Social Presence

TAM - Technology Acceptance Model

TPB - Theory of Planned Behaviour

TRA - Theory of Reasoned Action

UI - Use Intention

UTAUT - Unified Theory of Acceptance and Use of Technology

UTAUT 2 - Extended Version of the Unified Theory of Acceptance and Use of Technology

VIF - Variance Inflation Factor

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1. Introduction

The aim of this research is to develop user-centred study that proposes and tests a conceptual model to evaluate the influencing constructs of the acceptance of social robots in public spaces.

This first Chapter is organized in three sections: Section 1.1. introduces the problem context and the motivational aspects that trigger the present study, Section 1.2. describes the main objectives of this study and Section 1.3. presents the structure in which this document is organized.

1.1. Problem Context and Motivation

The field of robotics has been growing ever since it was first introduced, by General Motors, in automobile assembly lines, back in 1960's (Garcia et al., 2007). More recently, the available technology enables networked systems to be embodied and to socially interact with humans and perform a wide range of tasks in unstructured environments, *i.e.,* Social Robots. These robots might become the most immediate and intuitive bridge between humans and Information Systems (IS). This is due to the emerging trends as clouds and smart environments, that improve the robot's Artificial Intelligence data processing, and also, to the Internet of Things (IoT) concept, which enables the communication between every connectable interface in these environments (Lazzeri et al., 2018).

Therefore, social robots have shown to be successful in a wide range of application fields, especially in Healthcare and Therapy, in Education, in Domestic Environments and in the Workplace and Public Spaces (Leite et al., 2013). In the field of Healthcare and Therapy, facing the demographic phenomenon of the aging of the population with the aggravating problems of caregiver shortage as well as the constant increase in healthcare related costs (Broadbent et al., 2009; Heerink, 2010; Przywara, 2010), social robots are considered to be one viable solution for such challenges (Broadbent et al., 2009). Also, these systems might enable users to age independently in their homes, avoiding the traumatic and costly experience of aging in a nursery home. Furthermore, by decreasing the feeling of loneliness, the user's mental well-being might be improved. In the field of Education, for long, video educational agents have been used for pedagogical purposes, similarly, social robots are foreseen to have the same or even more educational benefits than these virtual teachers, mostly because of its social presence as an embodied robot (Leite et al., 2013). In addition, these robots have shown applicability in educational framework for children with special needs. For Domestic Environments the application of social robots on domestic environments has become evident. As time has become precious and as people's lives are busier than ever, consequently the time spent with family and friends decreases. To deal with this, increase its users' free-time, social robots for Domestic Environments are developed to perform tasks, to remind and advice, and to be used as an information source (Graaf & Ben Allouch, 2015). In the Workplace and Public Spaces, social robots have been tested and/or employed as guides, welcoming hosts, receptionists, promotors, waiters, among others.

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, Allouch, & Dijk, 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 that lead future users to adopt social robots, *i.e.,* 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 (Graaf et al., 2015). Hence, this study focuses on proposing an Extended Version of the UTAUT2 and testing it using Partial-Least Squares Structural Equation Modelling (PLS-SEM) to identify the most influencing dimensions of the acceptance of social robots by potential users, in a specific application field - Public Spaces. This way, the present study attempts to contribute to the field of social robotics by shortening a research gap and providing guidelines to future robot developers.

1.2. Dissertation Goals

The main goals of this dissertation are:

- To propose a conceptual model for the acceptance of social robots in public spaces, derived from the literature review, highlighting the constructs, the hypotheses and the indicators used for the measurement of the constructs;
- To test the proposed model in a sample of the Portuguese population, using the PLS-SEM methodology;
- To evaluate the moderating effects of age, gender and robot experience, in the model structure, using PLS-SEM multi-group analysis;
- To provide recommendations and guidelines for future developers of social robots for public spaces.

1.3. Dissertation Structure

This document follows the subsequent structure:

- **Chapter 1 - Introduction**
  This chapter briefly describes the problem contextualization and the motivational aspects which bring about the dissertation development, sets the main objectives and lays out the structure of the project.
- **Chapter 2 - Literature Review**
  Contains a brief history of robotics and a review of how recent robotics are growing, which explores the trends in technological innovation that enable the development of social robots. Furthermore, this chapter also explores several definitions of social robot and provides a review of literature focused on studies regarding HRI in the fields of application on which social robots are, or will be, most successfully employed. Finally, it addresses

the challenge of social robot acceptance by future users, exploring some of the most prominent models used for prior technology acceptance, and reviewing the available social robot acceptance literature.

- **Chapter 3 - Methodology**
  This chapter outlines the methods that were adopted in the dissertation. It details the proposed extension of the UTAUT 2 (Venkatesh et al., 2012), specific to the acceptance of Social robots in Public Spaces, providing the constructs and the way they are related (hypotheses), the questionnaire design and the data analysis strategy, *i.e.*, the techniques - essentially PLS-SEM related, to be used in the result analysis
- **Chapter 4 - Results**
  This chapter encompasses the application of all the methodology phases, proposed in the previous chapter, from the preliminary analysis (Section 4.1.) to the analysis of the preferences of the participants (Section 4.3.). The last section covers the discussion and the implications, practical and theoretical, of the main results.
- **Chapter 5 - Conclusions, Limitations and Future Work**
  The final chapter of this dissertation lays out the main conclusion withdrawn from the work performed and highlights the limitations encountered throughout the development of this thesis, as well as recommendations for future social robot acceptance studies.

2. Literature Review

This chapter, attempts to introduce the reader to the thematic of this dissertation, by providing a contextualization of the field of robotics and the necessary literature to propose and develop an acceptance model to be used in the present study. First it is presented the background, which includes a brief history of robotics, followed by a review of the trends in technological innovation that enable the development of social robots and a short analysis of the market of robotics. The second section explores the evolution in the definition of robot, accompanying the technical development and the rise of new systems, and explores the fields of application on which social robots are, or will be, most successfully employed. The third section addresses to the challenge of social robot acceptance. It opens with a review of some of the most prominent acceptance models in prior technology, followed by a review of social robot acceptance studies.

2.1. Background

Robotic systems have been in our society for at least 50 years. Notwithstanding, it was only over the last two decades, alongside major developments in technology, that robotic systems have started to be developed and employed outside the industrial world. Robots are now being employed in all kinds of markets, from construction to surgery, from public relations to domestic environments, and many more. In this first chapter of the literature review these thematic are discussed, presenting a brief summary of this evolution in the field of robotics, followed by a succinct analysis of the robotic market.

2.1.1. Brief History of Robotics

Robotics in general are already part of our society, but nearly a century ago the term “robot” did not exist. History shows that the term was either coined by Joseph Capek in 1917 in his short story “*Opilec*” defining automats or by his brother Karel Capek in 1921 in his play entitled “*Rossum's Universal Robot* ” defining a fictional humanoid created chemically (Hockstein et al., 2007). The term “*robot*” derives from the Czech word “*robota*” which means “*forced labour*”. According to Hockstein et al. (2007), the term remained attached to science fiction for a few decades and was mainly popularized by Isaac Asimov, a Russian-born American Writer and Biochemist.

Furthermore, in 1942 the United States started the Manhattan Project, with the objective of developing the nuclear bomb. The developers came across the major challenge of moving radioactive substances around, which led to the creation of the Telemanipulator. The Telemanipulator was the first robot ever built integrating the ability to receive input by motion and reproduce movement as output (R. Murphy, 2000).

Later, in 1958, General Motors introduced the Unimate - the first commercialized industrial robot - to assist in automobile production and ever since its first use on an assembly line in 1961, the application of robotics in the industry has exploded. The development of Industry Robots drove to debate what impact would these technologies have on employment, mostly derived by fear of mass unemployment (Royakkers & van Est, 2015). Although some jobs, such as lamplighter or ice-cutter, have been put aside by automation, there is no empirical evidence that this technological trend will differ from the previous technological changes, hence, creating and relocating jobs and changing the way some jobs operate (IFR, 2018). Industrial robotics have drastically changed the way factories operate, improving their productivity, being able to produce more, more efficiently, in less time and with less errors and improving safety in the workplace by performing tasks with risk of harmfulness for human beings, such as physically challenging tasks or tasks that required exposure to dangerous environments.

The technological evolution over the years made robots evolve from simple machines performing tasks that are considered undesirable, physically challenging or repetitive (Industrial Robot) into highly technologically advanced machines capable of performing tasks that require major precision (surgical robots) and, more recently, to meet social needs and new demanding markets (field and social robots). Darling (2012) argues that although robotic technology was strictly used in manufacturing for many years, nowadays the applications of robotic technology have spread across a wide range of areas, such as transportation, healthcare, education, military and entertainment. This occurred due to the need to shift from mass manufacturing to other types of more specific production processes, therefore there was a need to adapt industrial robots, developing new characteristics and abilities (Garcia et al., 2007; R. Murphy, 2000), leading to the development of a wide range of new technologies and the innovation of integrating different technologies in robotics. Later, with the arrival of new needs and markets such as cleaning, demining, construction, shipbuilding, search and rescue and agriculture, and with the aging of the population, demand in field and social robotics has been growing at a high pace and their

development growing accordingly, in order to supply these new markets and meet the social needs (Garcia et al., 2007). Royakkers & van Est, (2015), defend that Robotics, in general, develops new products according to the available IS, evidencing that the progresses made in robotics are in constant evolution.

According to Royakkers & van Est (2015), through robots, the internet has grown limbs and senses. Recent innovations in technology such as robotic grippers and arms, mobile systems, sensors, cameras, microphones and batteries, enable a networked system to be embodied and resort to these technologies, as well as the internet and AI systems and software, to process the gathered data in order to socially interact with humans and perform a wide range of tasks in unstructured environments. In other words, these recent technological innovations when integrated together enable the development of social robots. These robots might become the most immediate and intuitive bridge between humans and other IS, through emerging trends as clouds and smart environments, that not only improve the robot's Artificial Intelligence data processing, but also, through concept of the internet of things, enable the connection between every interface in these environments (Lazzeri et al., 2018).

More recently, Boston Dynamics has been focused on the development of autonomous mobile robots, disregarding HRI, presenting two different categories: Biped and Quadruped; All robots are able to move in rough terrains; The two biped robots: Handle, which resorts to wheels for movement and has two arms able to carry up to 45 kg and Atlas, which is the most dynamic humanoid robot ever built. This robot is able to run, jump over obstacles while running, grab objects and even perform perfect backflips. There are six models of quadrupeds, though we would like to note only the BigDog and Spot, both dog-inspired robots. BigDog is the first advanced rough-terrain robot, that is able to carry up to 45 kg of load through any terrain. Spot is a smaller version of the BigDog, and its latest version, SpotMini can be attached with a robotic arm, which allowed the robot to learn how to open doors (Boston Dynamics, 2019).

Also, Disney robotics presented a new robot in their Avatar-themed area inside its Animal Kingdom Park. This robot is an animatronic, that appears as one specimen of the Avatar fictional race and is considered to be the robot which has the most fluid human-like movements (TechCrunch, 2017).

Hence, mobility is considered a well-developed robotic field that resorts to the latest technology to successfully deploy systems that can move in unstructured environments, avoid obstacles, reach and explore places that can be harmful for humans, manipulate objects and perform several tasks. According to Garcia et al. (2007), research regarding social robotics has slightly shifted from locomotion and manipulation to HRI. Yet, when it comes to Human-Robot Interaction (in which AI plays the most important role), such as communication and social skills, *i.e.,* proximity, speech volume, speech recognition and interpretation, eye gaze, facial recognition, etc., there are still many challenges to be overcome. These challenges, inherent to the interaction between humans and robots, led to the emergence of the HRI research field. This field appeared in the mid-1990s and early 2000s, due to the frequent events/conventions regarding this area, researchers from diverse areas soon realized the need of working together to cover all this field

(Goodrich & Schultz, 2007). Therefore, HRI is multidisciplinary, requiring the study of such complementary fields as communications, computer science, engineering, psychology, and even theatre (Murphy et al., 2010). HRI is the area of Robotics that studies the understanding and the design of robots to be used by or with people, as well as their evaluation. Essentially, analysing the abilities of humans and robots, defining models of humans' expectations regarding the robot and designing the technologies, and providing the training required to establish expedient interactions are the critical elements of HRI (Goodrich & Schultz, 2007; Huang, 2016).

Robotics observed a great expansion when considerable progress was done in AI. AI is generally referred to as the science of making machines "think". The term was coined in 1956 in a meeting, that took place in the USA, with the purpose of studying how could machines be built to be intelligent and how would that impact our society. The term AI, leads to controversy as it is usually rises to debate whether a software can be as intelligent as a human or even superior, hence, there is no agreed definition to it (IFR, 2018; R. Murphy, 2000). Some authors suggest the following definitions for AI: *"The study of mental faculties through the use of computational models"* (Charniak & McDermott, 1985); *"A field of study that seeks to explain and emulate intelligent behaviour in terms of computational processes"* (Schalkoff, 1990). Essentially, AI must be perceived as the development of systems that not only integrate human-programmed processes but are also able to go beyond their predefined capabilities by learning, adapting, evaluating and making decisions.

Considering AI robotics, according to R. Murphy (2000) there is no need for a common and agreed upon definition of AI to approach AI Robotics, as the author argues that *"AI robotics is the application of AI techniques to robots."*. In other words, AI robotics is just the integration of AI software technologies to robotic systems, as the seven categories the Handbook of Artificial Intelligence suggests: knowledge representation, understanding natural language, learning, planning and problem solving, inference, search, and vision.

New robotics tend towards social robots, and with constant technology innovations these systems are progressively penetrating our society, starting by entering our households, workplaces and public spaces. AI enables robots to become social and interact with humans, recognizing, assisting and talking with their users (Wagenmakers, 2016).

2.1.2. The Market of Robotics: Industrial and Service Robotics

The International Federation of Robotics (IFR) divides robots into two groups: Industrial and Service, being the latter also subdivided in professional and personal robots. According to the IFR World robotics 2017, it is estimated that currently there are more than two million Industrial Robots in operation and this number is only predicted to grow even more, reaching over three million by 2020, considering a 14% annual growth between 2018 and 2020 (Figure 1).

The evolution of the annual supply from 2008 to 2016 has increased constantly, with an exception between 2008 to 2009. The respective forecasts for 2017-2020 predict 1.7 million new Industrial Robots, presenting a 15% annual growth. In addition to this, sales in 2016 reached 13.1 billion dollars, increasing 18% compared to the previous year. Figure 2 displays the 15 countries

that made the most purchases of Industrial Robots, and as it can be seen, the first 5 markets, China, Republic of Korea, Japan, United States and Germany aggregated represent 74% of the total sales volume in 2016. Since then, China is the country with the highest number of active industrial robots, which is expected to rise to 950 000 robots by 2020, much higher than the amount predicted for Europe - about 600.000 active units. Also, Japan and South Korea among other countries are estimated to expand their amount of active Industrial Robots, and consequently, the number of Industrial Robots in Asia alone is expected to grow up to about 1.9 million units by 2020, nearly the same as the worldwide stock of 2016.

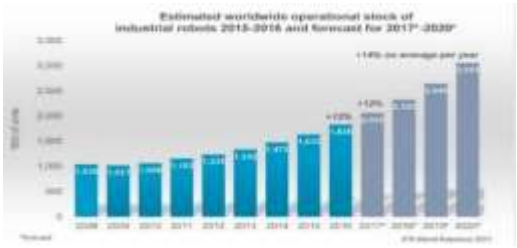

Figure 1: Estimated operational number of robots in the World, (Source: IFR World Robotics, 2017)

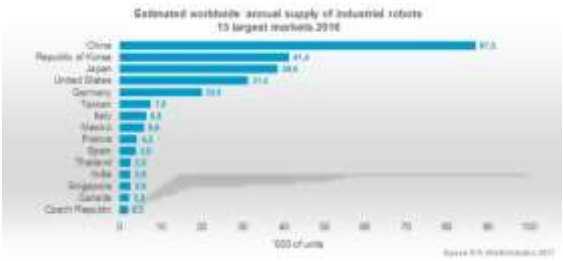

Figure 2: The 15 largest markets of industrial robots in terms of supply in 2016, (Source: IFR World Robotics, 2017)

Service robots are also growing at a high pace, and as previously mentioned, they are subdivided in professional service robots and personal and domestic service robots. Even though these two subcategories of service robots may appear similar, they serve different purposes. On one hand, professional service robots are produced and marketed for a business to business approach, therefore, they are typically more sophisticated and complex robotic systems, incurring in much higher unit value. On the other, personal service robots are developed for mass market, presenting more affordable prices and diffused through mainstream marketing channels

Starting with professional service robots, according to IFR World robotics 2017, although there was observed an increase in the number of robots sold in 2016, in comparison to the previous year, from about 48 000 to nearly 60 000 annual sales translating a 24% growth, the sales value only increased 2% reaching 4.7 billion dollars. There are four main application fields that represent more than 90% of total sales value (about 93% in 2016), which are medical robots, logistic systems, field robots and defence robots, accounting, respectively, for about 34%, 21%, 21% and 17% of the total sales values of 2016. However, these results do not translate the number of sold units. Considering logistic systems, in 2016 the number of sold units reached more than 25 000, which translates in a 34% increase from the previous year and represents more than 40% of the total sold units. This growth is even expected to increase, with forecasts estimating

nearly 190 000 units sold between 2018 and 2020, as observed in Figure 3. On the other hand, defence robots experienced a decrease of 25% in the sales value. This substantial decline in the demand of some defence robots, which are extremely expensive, was the main reason for such a low increase (2%) on the total sales value of professional service robots. As of 2016 11 100 units were sold, 100 less than in 2015. Notwithstanding, this number still accounts for 19% of the total of sales and is expected to grow at slow pace for the years to come. Medical robots account for the biggest portion of the total annual sales value of professional service robots. These robots are highly sophisticated and thus, present the highest prices in the market. With only 1 600 units sold in 2016, representing a 23% increase when compared to the 1 300 sold in 2015 (Figure 3), the sales of medical robots reached more than 1.6 billion dollars, which reflects on a unit price of more than a million dollars. The future of this industry is promising, and forecasts predict a continuous growth with sales over 10 000 units between 2018 and 2020. Although the previously mentioned types of professional service robots account for more than 90% of this market sales value, professional service robots for public relations have suffered the largest growth from 2015 to 2016, presenting increases of 133% in unit sales to 7 500 units and of 126% in sales value, reaching 119 million dollars. This reflects the potential success of social robots in professional environments. Even though some of the sold units are telepresence robots, the second most sold were guidance and information robots, which already require human-robot interaction through any type of communication, in other words, social robots. Forecasts predict a huge growth in this type of robotics, with sales expected to reach more than 65 000 units between 2018 and 2020, which is more than three times the estimated sales of the three previous years - around 21 000 units, as it can be observed in Figure 3.

Figure 3: Estimated number of Publlic Relations, Exoskeleton, Medical and Construction robots sold in 2015, 2016, 2017 and 2018-2020, (Source: IFR World Robotics, 2017)

The other type of service robots, personal and domestic service robots is also experiencing a great expansion, accounting more than 6 million units sold in 2016, presenting a 24% increase from 2015 and reaching a total value of about 2.6 billion dollars. Such results highlight the previously mention characteristics of the market of personal and domestic service robots - mass market and more affordable prices - as it presents the highest unit sales and the lowest sales value when compared to industrial robots and professional service robots, since most robots in this context are considered low-tech. Sales are recorded in two categories, service robots for domestic tasks, which include vacuum cleaning, lawnmowing and window cleaning robots among others, and service robots for entertainment and leisure purposes, counting with robot toys, hobby systems, education robots and research robots, etc. Domestic/household

robots, in 2016, reached more than 4.6 million sold units, an expressive 25% increase from the previous year. The IFR forecasts an even larger growth in 2017-2020, predicting more than 38 million sales during this period, as displayed in Figure 4. Considering entertainment and leisure robots, the sales reached 2.1 million units in 2016, translating an increase of 22% in comparison with the 1.7 million sold in 2015. Predictions indicate that for 2017 the predicted sales are around 2.5 million units and for the period of 2018 to 2020, this number will reach more than 10 million units, presenting a 20%-25% annual increase, as observed in Figure 4. Robots for assistance of disabled people or the elderly, in contrast with most of the previously mentioned robots are very sophisticated and complex, often presenting social robot's characteristics and therefore present lower sales. However, this market is growing and is expected to continue growing, presenting an increase from 2015 of 13%, with more than 5 000 units sold and with forecasts expecting sales to reach more than 32 000 units in the period of 2018-2020.

Figure 4: Estimated number of household and entertainment robots sold in 2015, 2016, 2017 and 2018-2020, (Source: IFR World Robotics, 2017)

2.1.3. Background Summary

Having summarized the evolution of robotics and briefly analysed the market of robotics, it was observed that the evolution of robotics is towards intelligent systems, which allow the employment of robotics across many, mostly increasing, markets. This evolution affected not only these most recent emerging markets of robotics, but also the old ones such as industrial robotics.

It is evident that AI takes the most important role in this new era of robotics, where mobility, sensory and vision capacity challenges have been surpassed. 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 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 currently presenting around 2 million operational units, with an expected increase up to 3 million by 2020. Nonetheless, it is in the service robotics market that the growth is even more evident. Profession service robots, especially Public Relations and Logistic Systems presenting, respectively, increases of 133% and a 34% in units sold in 2016, in comparison with the previous year. Also, the personal service robots for households and for entertainment presented increases around 20-25%. Such results, especially the abrupt increase of units sold in 2016 and expected to be sold in the period of 2017-2020 of public relation professional service robots, appear to

indicate that the acceptance of such social robotic systems, passes through the introduction of them in our society by organizations.

As this study is focused on social robots, the Section 2.2., aims at providing a definition for social robot and reviewing the application fields where they are or will be most successfully employed, in light of the available literature regarding such robotic systems.

2.2. The Social Robot

Royakkers & van Est (2015) suggest that recent Robotics is inspired by two technological objectives*: " (…) the engineering dream of building machines that can move and act autonomously in complex and unstructured environments."* and *" (…) the dream of building machines that are capable of social behaviour and have the capacity for moral decision making."* Although such system has not yet been developed, social robots are entering our society (Graaf & Ben Allouch, 2015). In this section a definition of social robot based on research findings will be described, followed by a review of literature focused on studies regarding the fields of application in which social robots are or will be most successfully employed: (1) Healthcare and Therapy, (2) Education, (3) Domestic and (4) Workplace and Public Spaces (Leite et al., 2013).

2.2.1. Defining Social Robot

As previously observed in Section 2.1., Robotics have evolved abruptly over the last years and therefore, the definition of the term "*robot*" must adapt to fit accordingly with the evolution of robotic technology. When robots were introduced, the Robot institute of America defined it as: "*A reprogrammable, multifunctional manipulator designed to move material, parts, tools, or specialized devices through various programmed motions for the performance of a variety of tasks"*. This definition perceived robots as machines built to execute tasks and was only appropriate for industrial robots. With the increasing evolution of service robotics, a new definition was needed for these robotic systems. The IFR suggested the following definition of Service Robots: "*A robot which operates semi or fully autonomously to perform services useful to the well-being of humans and equipment, excluding manufacturing operations"*. Even though some social robots can be considered service robots, others, for instance with entertainment purposes are not. For a robot to be considered social, it must interact through some sort of communication (*e.g.* natural language, gestures, text on a display, facial expressions) (Bartneck & Forlizzi, 2004). Therefore, and considering the increasing interest and the growth in the social robot development over the last two decades, a new definition was required to address this specific type of robots.

Darling (2012) broadly describes a social robot as *"a physically embodied, autonomous agent that communicates and interacts with humans on a social level."* According to Graaf et al. (2016), most definitions of social robots agree that these robots are a type of robot that can interact and communicate socially in a way that is similar to humans. Still, descriptions of what "*a similar way to humans*" is, are quite unclear and vague. Addressing this subject, Bartneck & Forlizzi (2004), suggested that a social robot is *"an autonomous or semi-autonomous robot that interacts and communicates with humans by following the behavioural norms expected by the*

people with whom the robot is intended to interact" and even though it provides a clearer definition of a social robot's behaviours and actions, *i.e.,* the previously mentioned "*similar way to humans*", existing social robots are still limited when considering the integration of human social skills (Graaf et al., 2016).

Breazeal (2003b) defines social robots as a type of autonomous robots that people address social models to, in order to be able to interact with and understand them, emphasising that even with non-autonomous systems (cars, computers, etc.) people tend to apply social or mental models, such as anthropomorphising to justify, comprehend and foresee its behaviours. Also, the author categorises social robots in four levels according to their sociability*: socially evocative, social interface, socially receptive and sociable*. Following this work, Fong et al., (2003) added three more classes to the former: *socially situated, socially embedded* and *socially intelligent*. In this article, the authors present the term *"Socially Interactive Robots"* (SIR) to address robots whose main purpose is social interaction with humans presenting such capabilities as: understanding and/or expressing emotions and natural cues, communicating in high-level conversation and developing relationships, manifesting personality and character as well as learning/developing social skills. However, such systems are far from being developed and there is a need to acknowledge that social robots are not, in reality, social. Yet, they 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 for social robots, which was considered the most appropriate one: *"robots that elicit social responses from their human users because they follow the rules of behaviour expected by their human users".*

2.2.2. Social Robot Application Fields

A. Health Care and Therapy

Social robots have a tremendous potential in the health care and therapy (Leite et al., 2013). "*Socially Assistive Robotics*" (SAR) (Feil-Seifer & Matarić, 2005) is the most used term given to these systems and they have been demonstrating their success and application in the fields of elder assistance, autism related therapy, and in other services, such as behaviour coaching (Breazeal, 2011) and rehabilitation (Matari et al., 2007). Feil-Seifer & Matarić (2005) define SAR as the conjunction of "*Assistive Robotics*" , *i.e.,* any robotic system that helps and gives support to a person, and SIR (Fong et al., 2003). In Matari, Eriksson, Feil-Seifer, & Winstein (2007) the authors state that the goal of this robotic field is to *"augment human care and existing robot-assisted hands-on therapy toward both improving recovery and health outcomes and making the therapeutic process more enjoyable."*

One of the main motivations for the development of these systems is the demographic phenomenon of the aging of the population, as the lifespan is increasing worldwide, mostly due to medical advances and to the significant amount of countries that is experiencing decreases in birth-rates (Breazeal, 2011; Chu et al., 2017; Dautenhahn et al., 2015). In addition to that,

industrialized countries are facing a shortage in labour, even more critical in the healthcare sector that is expected to worsen over the years (Heerink, 2010). Also, healthcare related cost for the elderly are continuously increasing according to Heerink (2010) and Przywara (2010). Consequently, due to this aging of the population and the labour shortages industrialized countries face, either the number of caregivers available will not be enough or their cost will be too high, and therefore not affordable for the vast majority of people. Hence, *"there is a growing necessity for new technologies that can assist elderly in their daily living."* (Broekens et al., 2009). If appropriately applied, these system might be the solution to the above mentioned issues providing aged-care the best way they can, being helpful to caregivers, by easing some of the work, focusing on more crucial tasks (Lehoux & Grimard, 2018), and possibly decreasing care expenses and increasing robot acceptance (Shishehgar et al., 2017).

Social robots for companion of the elderly have the purpose to improve their health and mental well-being, as keeping the user actively engaged in interaction may help people with dementia. Also, by acting as a companion, their presence might help decrease the feeling of loneliness. Although other robots can serve as social companions, this type of robots are often designed to be perceived as pets, for situations where owning a pet would not be appropriate, either because it is not allowed or because some people might not be able to take care of a real pet (Fischinger et al., 2016; Kachouie et al., 2014; Robinson et al., 2014). Examples of these robots are the seal robot Paro and AIBO (Figure 5).

Kramer et al. (2009) developed a three week experiment comparing interactions of dementia patients with real dogs to interactions with AIBO (Figure 5), and noticed that in some trials, the interactions with AIBO lasted longer and with more effect. Similar results were presented by Giusti & Marti (2006), as most of the participants spent a considerable amount of time talking to Paro and talking to others about Paro, verifying the improvement in social interaction between residents and keeping them interactively engaged, possibly increasing psychological well-being. More recently, Chu et al. (2017) performed experiments over five years with 139 dementia patients to observe their interaction with two PaPeRo robots (Figure 5), that were named "Jack" and "Sophie", with considerable more capabilities than pet-robots, such as communication and some social functions. Results were in accordance with the previously mentioned studies. Henceforth, research showed that social robots have a positive effect on patients with dementia, improving communication and keeping the patients socially active.

Social Robots have also shown applicability and positive effect in autism related therapy. Dorothée et al. (2009) performed a series of 10 trials with six children. The trials were a 40 minute play session with AIBO - Figure 5. Results showed that the children developed a higher level of interaction and interest over time and more inference towards the dog robot when compared to a real dog, even showing occasional displays of affection to the robot. With similar results Michaud et al. (2007) ran a study with a teleoperated robot, verifying that more attention was given to the robot than to a human being. Other studies have been performed in an Educational context for children with Autistic Spectrum Disorder (ASD) (Billard et al., 2006; Lytridis et al., 2018; So et al., 2017), which will be highlighted in Subsection B. Education.

As research shows, elder people would rather live independently in their homes than in a Care Home (Gitlin, 2003). The concept of an old person living independently is usually referred to as “aging in place”. Aging in place requires an individual to perform daily tasks and to perform the maintenance of his home, which can be hard for a vast amount of older adults and getting harder over the years, as some of these daily tasks may actually become challenges (see more in Fausset et al., 2011). More recently, SAR has been highlighted as one solution to support the elder in “aging in place” and has received substantial attention regarding this issue (Fischinger et al., 2016; Shishehgar et al., 2017), reducing loneliness, performing household tasks, preventing accidents and enabling a more frequent evaluation of the person’s condition to their family or doctors. In Fischinger et al., (2016), the authors consider that robotics research divides into three categories regarding assistive robots for the elderly: social companion robots, household service robots and telepresence systems, and present the development of a care robot for the elder that encompasses these three categories. The robot was called “Hobbit- The mutual Care Robot” - see Figure 5. This project was funded by the European Union and started in 2011 with 36 months of duration. Hence, Hobbit should provide capabilities such as emergency detection - autonomously search for the user after a period of inactivity -, acting on emergencies - automatically contacting the family or the hospital - and fall prevention measures - clearing the path for the user by removing obstacles. Also, it can perform video calls, remind the user of its medication or appointments and presents entertainment features such as games, books, music, among others.

Figure 5: Some of the robots used in Healthcare and Therapy studies: From left to right - Paro, AIBO, PaPeRo and Hobbit

B. Education

Another sector where social robots have been found successful is in Education (Mubin et al.,2013). For long, video educational agents have been used for pedagogical purposes. Social robots are foreseen to have the same or even more educational benefits than these virtual teachers, mostly because of its social presence as an embodied system (Leite et al., 2013). Furthermore, social robots were also found successful in an educational framework for children with special needs (Billard et al., 2006; Janssen et al., 2011; Lytridis et al., 2018; Serholt, 2018; So et al., 2017).

Kanda et al. (2004) conducted a field trial in a Japanese elementary school to evaluated the interaction between hundreds of fifth and sixth graders and two identical robots “*Robovie*”, see Ishiguro et al. (2001) - Figure 6 for two weeks. The objective of the experiment was to improve

Japanese children's English skills by playing and communicating with "*Robovie*" outside the classroom. Results show that, even though the robots failed to keep students engaged after the first week, not nearly reaching students' expectations, students who interacted with the robots for the whole experience period eventually improved their English skills.

Considering that education for children with special needs involves great expenses, and therefore is not affordable for everyone leading to unfulfilled demand, social robots, such as NAO (Figure 6) or Pepper (Figure 9) , have been suggested to integrate these children's pedagogical development as a less expensive solution (Lytridis et al., 2018). Although there are some educational social robot projects for children with other chronic diseases, such as ALIZ-E (a reprogrammed NAO robot - Figure 6) for diabetes (Janssen et al., 2011), a large portion of research in the special educational context focuses on Children with ASD. This disorder has many degrees and it is expressed in many different ways, yet it usually affects communication, either verbal or non-verbal, social interaction and social skills, creativity (Ferrari et al., 2009), delay in the recognition of gestures and facial expression and impairments in interpreting attitudes and emotions of other people (So et al., 2017). With such impairments, autistic children frequently present learning difficulties. In addition to that, Lytridis et al. (2018) notes that children with ASD generally have positive attitudes towards robots and that the benefits of the application of robots in these children's development include increased interest, concentration and attention and also the development of new social behaviours. Therefore, social robots have been found to be successfully applied in education and social development of children with ASD.

As play is considered to be an important driver in the learning process and social development of children, and children with ASD tend to be limited when it comes to this activity, the use of social robots as play partners and tutors has been found proficient, with positive effects on children with ASD (Dorothée et al., 2009; Ferrari et al., 2009). To demonstrate such effects, Ferrari et al. (2009) conducted a trial with 6 children with ASD. This trial makes use of the IROMEC robot prototype, displayed in Figure 6 to interact with these children, leading them into several games. The games were developed with the objective of improving children's communication and interaction, motor, cognitive and social skills. The trial underwent a Wizard of oz experiment, as the robot was controlled remotely. Results verify that the children were engaged with the robot and enjoyed interactions with it, as well as with the present humans, observing that most objectives were fulfilled, as children had to take turns (interaction with others and social skills), had to clap their hands to control some robot features (motor skills) and had to learn and follow the game rules (cognitive skills).

More recently, So et al. (2017) conducted a study to evaluate the effects of teaching gestural recognition and production to children with ASD with a social robot, NAO, see Figure 6. The results showed that a social robot can be employed proficiently to teach gestural recognition and production to children with low functioning ASD, *i.e.,* children with cognitive impairments, even though the subjects showed a lot more progress in the recognition than in the production of gestures.

Figure 6: Some of the Robots used in Education Studies: From left to right - Robovie, NAO and IROMEC

C. Domestic

Social robots are expected to increasingly penetrate our homes. In order to be useful in such environments, according to Walters et al. (2007), social robots must execute a wide variety of useful services or actions effectively and perform them in a socially adequate and natural way for its users. In a domestic context, social robotics research has gathered a substantial amount of focus over the last years (Leite et al., 2013). However, most studies focus on short term experiments, usually of one day (Graaf et al., 2015), which only provides answers to user's initial adoption, not enabling human-robot interaction beyond de novelty effect, *i.e.,* the user's first impressions and reactions to technology. On the other hand, longitudinal studies allow researchers to evaluate the evolution of the user's post-adoption phase of a technology, where it can be observed whether users actually use or not a technology (Graaf et al., 2014). However, there are only a few long-term studies considering a domestic context (Graaf et al., 2015) and the majority of them resorted to commercially available robots (some non-social), since most research prototypes are not safe for conducting long term human-robot interactions outside the lab, due to their instability (Fernaeus et al., 2010; Leite et al., 2013).

Forlizzi & DiSalvo (2006) performed an ethnographic study with Roomba, the vacuum cleaning robots, with the objectives of evaluating how the integration and usage of a service robot in a domestic environment would affect cleaning routines, and how would a service robot adapt to the dynamics of domestic environments. In this study the authors ran two separate sets of surveys, each relating to the previously mentioned objectives. The research was conducted over four months in 14 households and results show that although expectations were not met as most participants assumed the robot was intelligent, capable of acknowledging the surroundings and adapt to the domestic environment, in the majority of the households the robot was well integrated and frequently used, and most participants were surprisingly pleased with its effectiveness. Roomba changed most floor cleaning procedures and even developed a rapport with some participants, enabling users to perform another task (multi-tasking) and increasing both planned and convenience housekeeping tasks, and making the cleaning tasks social activities, mostly to families, as well as acting as a partner in the housekeeping tasks, for instance, some participants moved the furniture or pre cleaned some surfaces to increase Roomba's performance.

With another type of robot, more specifically with Pleo, displayed in Figure 7, a Dinosaur Robot toy, Fernaeus et al. (2010) conducted a similar study. The robot was installed in six family homes for 2 to 10 months (duration chosen by the participants) and, depending on the chosen period, families were interviewed more than twice to evaluate if Pleo was able to meet or not the user's expectations. Results show, that even though the expectations among the participants started quite high, essentially due to the robot's cost, complexity and successful marketing practices, the robot's performance was unable to keep these expectations. Notwithstanding that at first, the families started approaching Pleo like a real pet (naming and petting it), immediately after the novelty effect wore off, the robot failed to engage its users and soon started to be treated like a toy, only being turned on for special occasions or just for a play activity.

More recently, Graaf et al. (2014) performed a long term study with a rabbit-shaped communication robot, Karotz (Figure 7), to evaluate how the use of social robots at home for an extended period of time affects the usage of social robots in the long-term. The robot was placed in 70 households for a period up to six months. This included 160 participants of which 102 were able or willing to answer to questionnaires. This experiment observed that the robot failed to engage with the users as more than half of the participants in the end either, never used it or, resorted to it less than once a week, and due to the failure in meeting the participants' expectations, as most did not find the robot useful and expected it to be more intelligent. Nonetheless, this study indicates that pre-adoption is influenced by how people perceive their lives with a robot and by their experiences and attitudes towards robots and other technologies. On the other hand, on a post-adoption phase, people look more into the usefulness and enjoyment of the robot.

Figure 7: Some of the robots used in Domestic Studies: From left to rigt - Pleo and Nabaztag/Kartotz

D. Workplace and Public Spaces

Social robots have also shown their application in public spaces and in the workplace. They have shown positive effects and have been suggested to be employed in offices (Veloso et al., 2012), hotels (Pinillos et al., 2016), airports (Triebel et al., 2016), University Campus (Gockley et al., 2005) and malls and stores (Foster et al., 2016; Shi et al., 2016). Research suggests that for social robots to be successfully applied in these environments, they must be able to adjust their behaviour in accordance to the user and to unstructured environments and unexpected scenarios (Leite et al., 2013).

Gockley et al. (2005) developed a robot receptionist, Valerie (Figure 8), which was introduced in the Carnegie Mellon University (CMU) campus for a nine-month field study with the purpose of evaluating long-term human-robot relationships to better understand how a robot can

get and hold the users' attention for an extensive period of time. The robot had the capacity of giving directions and reporting some news or weather forecasts, also, it was integrated with a personality and background story, which was expressed to users through monologues. Results notice that after some time, even though a few users interacted daily with Valerie, most of them only interacted for 30 seconds or less. Observing these results, the authors suggested some improvements such as greeting ovation and behaviour, interactive dialogue, emotion expression and regular user identification.

The CMU's CORAL research group, directed by Manuela Veloso focuses on studying robots that Cooperate, Observe the World, Reason, Act and Learn (CORAL). In 2009 the group started the development of CoBots (Collaborative Robots), *i.e.,* mobile multi-floor service robots, built to perform several tasks and interact with humans and other robots in indoor environments (Veloso et al., 2012) - Figure 8. According to Veloso et al. (2015), CoBots were developed to achieve three main capabilities: autonomously move around the several indoors environments and avoid obstacles (furniture, people, etc.), efficiently schedule tasks, by sharing information between robots, and proactively ask for help from people (Symbiotic autonomy). Tasks include "*Go-To-Room*" tasks (the robot is assigned to go to a specific location), which can be considered as a "*Deliver-Message*" task, if the CoBot is also assigned to deliver a message. Also, the CoBots can transport objects in their basket *"Item Transport Task*", but cannot manipulate objects (yet), therefore they must ask humans to place the respective items to be carried in their basket. The CoBots can also perform "*Escort tasks*" by waiting, welcoming, guiding and accompanying someone to a location. Finally, the CoBots are also able to serve as telepresence robots, in a semi-autonomous way (Veloso et al., 2012).

Pinillos et al. (2016) developed a long-term evaluation of Scarino, an interactive bellboy robot specifically designed for hotels, with the goal of improving the robot's capabilities and thus increasing its acceptance. Scarino is an autonomous robot that accompanies guests, provides useful information about the city and about the hotel and performs tasks such as guiding guest to rooms or restaurants and calling them transports, and, when not needed, Scarino is designed to be charging in the lobby. During the experiment, the robot was improved twice, once after the first feedback and one after the second. Improvements were made in the posture, behaviour and in the speech, in the microphone quality for better speech recognition, the tablet size was increased for a more comfortable proximity to the robot, in the navigation routes, even including the readjustment of furniture and more. Results show that the improvements were successful, observing that the usage of the robot increased, alongside the average of daily users and with interaction time, at first with an average of 1.54 minutes, which rose up to 2.58 minutes. In terms of performance, the robot started with only a 72% of accomplished tasks, rising to 88% by the end.

Figure 8: Some of the robots used in Workplace studies: From left to right - Valerie, Cobots and Sacarino

Weiss et al. (2008) presents a study consisting on a breaching experiment. In this study a robot, ACE, was introduced in the streets of Germany to confront pedestrians during their daily lives. The study resorted to a UTAUT based questionnaire to gather data from participants that interacted with the robot. However, data was analysed simply by observing the means of the answers. The main results of this study indicate that there was a positive acceptance of the robot.

Later, Kanda et al. (2010) developed a robot to be employed in a shopping mall, with the capacities of guidance, relationship building and store advertisement. In this study, the authors conducted a field trial in a real shopping mall. The experiment had the duration of about one month with the purpose of testing the robot on the field. The robot engaged in 2642 interactions with 235 participants, who carried RFID tags to improve engagement in repeated interactions. Results show that the robot successfully performed its objectives, guiding was shown proficient, considered to be detailed, accurate and understandable. Rapport building was observed during the experiment, with participants finding the robot "*friendly*" and noticing that it knew their names due to their RFID tags, and it was observed that the robot influenced the participants' shopping behaviour as most participants either bought, visited, ate or saw something that was mentioned by the robot.

In the study presented by Weiss et al., (2015), a user-centred development study of a social robot, IURO (Figure 9), was conducted in Munich. For this, a field trial was performed, where the IURO was placed on the ground, to ask participants for directions. The interactions were videotaped and later analysed, in addition, to evaluate the acceptance and the expectation of potential users, three questionnaires were used, one to explore usability, one for user experience and the last to estimate acceptance. The methodology and the results were in line with the previously mentioned study Weiss et al. (2008), thus indicating a positive acceptance of this social robot in public spaces.

Triebel et al. (2016), developed Spencer, a robot resultant of an EU-funded project involving six Universities and two industrial partners, being one of them KLM - Figure 9. The project started in April 2013 with 36 months of duration. This robot was developed to assist, inform and guide passengers in large and busy airports. Also, the robot has the particular task of guiding passengers of connecting flights conveniently and efficiently from their arrival gate to the passport control.

Shi et al. (2016) conducted a study with a robot acting as an advertiser for three stores and in two of them the results went accordingly with the previously mention study, as it was observed an increase in the number of store visits when the robot was installed

MuMMER (MultiModal Mall Entertainment Robot) is a four-year project started in March 2016, which is funded by the EU and has the objective of developing a social robot with SoftBank's Pepper (Figure 9) as their baseline, that is able to engage autonomously in social communication with shoppers in a mall, to improve their shopping experience (see Foster et al., 2016, for more detailed information). A recent publication from this project, more specifically, Niemelä et al. (2017), provides the first results of the field trials taking place in Ideapark, a shopping mall in Finland. Results were drawn from two surveys, one before and the other after the introduction of the robot in the mall. Even though most of the participants found the robot friendly, fun, charming and safe, with some of them even perceiving it as a living entity capable of expressing emotions, a large portion (more than one third) considered the interaction to be rather odd than natural. Hence, it was observed a high acceptance of the robot in malls, however such positive results may be explained by the short duration of the trial, disregarding the evaluation of long-term interaction, beyond the novelty effect.

Figure 9: Some of the robots used in Public Spaces studies: From left to right IURO, Spencer and Pepper

Since 2018, the company Beltrão Coelho has been acting as the distributor of social robots for the workplace and public spaces in Portugal. Their business model is only focused on rental services of two social robots: Sanbot (Qihan) and Cruzr (Ubtech) - Figure 10. These robots are expected to work in events, retail, museums and exhibitions, and hotels. Their main roles are of promotor, information source and guide. In addition to this, a social robot has been implemented by the Portuguese government in one Citizen's Bureau in Porto, since January 2019, as an attempt to improve the quality of the services offered - Figure 10. This was a measure implemented by Simplex, a national program for the simplification of administration and modernization of public services. The robot was named "Lola" and it is expected to work as a personal assistant, interacting with citizens to give information about and guidance to, their intended services.

Figure 10: Social Robots recently introduced in Portugal: From left to right Sanbot, Cruzr and Lola

2.2.3. Social robot review Summary

As observed in the health care 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. 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, such as picking something of the floor. 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, *i.e.,* as living beings, was mainly achieved, and long term engagement was found positive in most experiments. This is probably due to the cognitive limitations of the users (children, children with ASD, the elderly and dementia patients).

In the workplace and in public spaces, research notices that when employed in public places, social robots present a high level of user acceptance (Kanda et al., 2010; Niemelä et al., 2017). 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. On the other hand, social robot acceptance seems to lower over time. This was immediately noted in a hotel environment (Pinillos et al., 2016), where guests stay usually for short periods of time. Even though results improved with the changes on the robot over time, the usage rate was still very low, as the robot was only busy for 12% of the time he was operational. 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 (students and university lecturers) is 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 & Ben Allouch, 2015), the application of such systems at homes is not yet visible and studies often show low engagement and 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, emphasizing the influence that utilitarian factors, such as usefulness and ease of use, have on social robot acceptance.

As observed, social robots are considered to be successfully employed in the fields of healthcare and therapy, education, domestic and workplace and public spaces, however, research shows that most existing social robots either present a low usage frequency and consequent low acceptance levels in long-term interactions or have not been evaluated under such unstructured conditions. Also, social robot acceptance generally decreases on the long term, after the novelty effect wears off. Therefore, developers must understand how users interact, with social robots, *i.e.,* through a user centred development approach (Graaf et al., 2014; Leite et al., 2013; Pinillos et al., 2016). This way, developers may gradually improve these robots towards better engagement rates, not only improving the robots technical abilities such as navigation, vision, sensing, among others, but also the robot's social behaviour, such as the approach distance, appearance, stance, volume of the voice, among others. (Walters et al., 2007). The following section, addresses to user-centred studies, reviewing both the most important studies that investigate acceptance of prior technologies, and the ones that explore the acceptance social robotics.

2.3. Towards the Acceptance of Social Robots

With the purpose to ease communication, Social Robots are developed for Human-Robot Interaction in a social way, thus, increasing human acceptance (Breazeal, 2003a). However, research indicates that the exposure to robots does not immediately influence positively the acceptance of these technologies nor the readiness to engage in interaction with them (Kato et al., 2005). Having thus observed, throughout Section 2.2., that social robots are expected to become ubiquitous in society, showing applicability throughout a wide range of areas, such as Healthcare and Therapy, Education, Domestic and Workplace and Public Spaces. Notwithstanding, the existing social robots still behave in a quite limited and predictable manner, often showing a decrease in their acceptance by humans beyond the novelty effect. Thus, social robot acceptance has become one of the major challenges in the HRI field. Therefore, it is essential to integrate future users in the initial processes of the development of social robots (Graaf et al., 2016). Social robot acceptance methods are mainly influenced by acceptance studies on prior technologies. Therefore, Section 2.3.1. presents the state of the art of the acceptance models in prior technologies. Then, Section 2.3.2. provides a literature review of social robot acceptance studies, followed by a summary in Section 2.3.3.

2.3.1. Acceptance of Prior Technology

Explaining human acceptance of computers was also one of the most crucial research challenges in the fields of IS and Human-Computer Interaction (HCI) (Venkatesh & Smith, 1999). Some researchers studied how usage behaviour was influenced by internal beliefs and attitudes, mainly reaching inconclusive results, due to the lack of adequate theoretical or psychometric justification employed in the proposed variables of these studies. Others proposed resorting to social psychology intention models, such as the Theory of Reasoned Action (TRA) (Ajzen & Fishbein, 1975) as a baseline for further research on computer acceptance (Davis et al.,1989). Thus, some of these behavioural models were used to study user acceptance of IS, such as one of the

successors of the TRA, the Theory of Planned Behaviour (TPB) (Ajzen, 1985, 1987), displayed in Figure 11. This model has been found to be a reliable tool to predict usage and use intention of IS (Mathieson, 1991). According to the TPB, a specific behaviour is determined by the individual's intention to perform this behaviour and perceived behavioural control. In turn, this behavioural intention is directly influenced by an individual's attitude towards this behaviour, *i.e.,* the feelings (positive or negative) of carrying out a behaviour, by subjective norm, *i.e.,* how an individual perceives what other significant individuals will think of him by performing a behaviour, and by perceived behavioural control, *i.e.,* how an individual evaluates the internal and external conditions that facilitate/impede a behaviour (Ajzen, 1985; Mathieson, 1991).

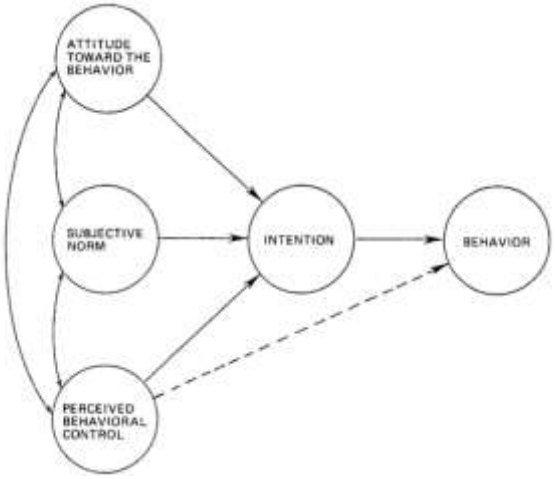

Figure 11: Theory of Planned Behaviour, from Ajzen, 1985 (Source: Ajzen, 1987)

However, the most used model in these studies is the Technology Acceptance Model (TAM), developed by Davis (1985). The TAM (Figure 12) is an adaptation of the TRA that was built to estimate the acceptance of an IS. According to Davis et al. (1989), the TRA *"is an especially well-researched intention model that has proven successful in predicting and explaining behaviour across a wide variety of domains"*, as it was built to describe practically any human behaviour. Consequently, it could be applied, as a special case, to study the variables that influence the usage behaviour of computers.

The TAM resorts to the TRA as a baseline for theoretical justification of the connections between its two key beliefs, Perceived Usefulness (PU) and Perceived Ease of Use (PEOU), and Usage Behaviour/Actual Use, through the user's Attitudes and Behavioural Intentions towards use of an information system (Davis et al., 1989). PU considers a person's belief that using the system will improve his/her performance and PEOU refers to the lack of effort the usage of the system may provide to the user. Attitude Towards Use is perceived as the user's evaluation of his/her desire to use the system.

This theory assumes that an individual's acceptance of IS is determined by the Actual Use of this system, which is estimated by the users' Behavioural Intention to use a system. Behavioural Intention to use a system, is determined by PU and by Attitude Towards Use. In turn, this construct is determined by PU and PEOU. Also, the model considers that PU is influenced by PEOU, and that external variables influence Behavioural Intention to use through PU and

Attitude Towards Use (Davis et al., 1989; Y. Lee, Kozar, & Larsen, 2003; Mathieson, 2014; V. Venkatesh & Davis, 2000).

This model is considered one of the most influential and widely applied theory for predicting human acceptance of IS (Y. Lee et al., 2003). According to Venkatesh & Davis (2000), during the 1990s, the progress done in the IS field, particularly in the issue of understanding and predicting user acceptance of IS was substantial, especially complying with the TAM. This was reflected in the large amount of theoretical and empirical studies that were developed based on the TAM during this period, proving success of this model. Most of these empirical studies' findings suggested that the TAM was consistent, explaining a significant value in the variance in usage intentions and consequent usage behaviour (usually 40%). Also, this theory is quite broad and can be applied to various technologies, such as word processors, e-mail and the World Wide Web (WWW), among others, in different situations, with different subjects and external factors to validate its robustness to its defenders (Y. Lee et al., 2003).

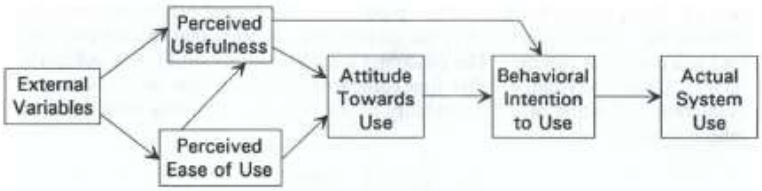

Figure 12: Technology Acceptance Model (TAM), from Davis et al., 1989
(Source: Mathieson, 2014)

Alongside the TAM, other models for the acceptance of technology were developed over the years, such as the Motivational Model (MM), the Combined TAM and TPB (C-TAM-TPB), the Model of PC Utilization (MPCU), the Innovation Diffusion Theory (IDT) and the Social Cognitive Theory (SCT), which were all combined into the Unified Theory of Acceptance and Use of Technology (UTAUT) alongside with the TRA, the TPB and the TAM (Venkatesh et al., 2003). The UTAUT agglomerates the most significant constructs of the eight, aforementioned, technology acceptance models into a unified model with the purpose of understanding the levels of acceptance and usage of new technologies, hence, contributing to the development of such systems. This model, as the TAM, assumes that Behavioural Intention determines Usage Behaviour which is, consequently, how the acceptance of technology is measured. The model is composed by three main components that directly influence Behavioural Intention - Performance Expectancy, Effort Expectancy and Social Influence; and one that directly influences Use Behaviour - Facilitating Conditions (Figure 13). In turn, these four main components are influenced by the moderating factors - Gender, Age, Experience and Voluntariness of Use (Venkatesh et al., 2003).

Performance Expectancy is defined as *"the degree to which an individual believes that using a system will help him or her to attain gains in job performance"*. This component is the result of the combination of five components of different models, specifically PU (TAM and C-TAM-TPB), Extrinsic Motivation (MM), Job-fit (MPCU), Relative Advantage (IDT), and Outcome Expectations (SCT).

The second component, Effort Expectancy, is defined by the authors as "*the degree of ease associated with the use of the system"* and is the result of three components, from different models, that relate to this component: PEOU (TAM), Complexity (MPCU) and Ease of Use (IDT).

The third component, Social Influence designates *"the degree to which an individual perceives that important others believe he or she should use the new system".* This component was based on three constructs from previous models: Subjective Norm (TRA, TPB and C-TAM-TPB), Social Factors (MPCU), and Image (IDT).

The last component, Facilitating Conditions is described as "*the degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system".* This was built by taken under consideration Perceived Behavioural Control (TPB, C-TAM-TPB), Facilitating Conditions (MPCU) and Compatibility (IDT). This component is the only one that does not directly influence Behavioural Intention, instead it is a direct determinant of Usage Behaviour (Figure 13).

Williams et al. (2015) performed a systematic review of 174 articles on the UTAUT model from various fields such as: communication, general-purpose, office, and specialized business systems, and found that the four main components of the UTAUT explain about 70% of the variance of Behavioural Intention, which surpasses all the eight models in which it is based on, that only explain between 17% and 53% of the variance of Behavioural Intention (Venkatesh et al., 2003).

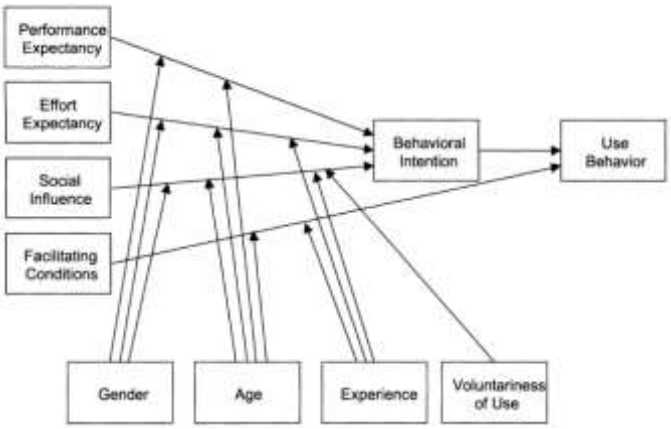

Figure 13: Unified Theory of Acceptance and Use of Technology (UTAUT), from Venkatesh et al., 2003; (Source: ibid.)

The extended version of this model, the UTAUT2, completes the latter by (1) adopting the existing constructs and add three new ones to a different context, *i.e.*, consumer, instead of employee acceptance of technology, (2) changing and introducing influences between variables. Thus, Performance Expectancy was defined as "*the degree to which using a technology will provide benefits to consumers in performing certain activities",* Effort expectancy as "t*he degree of ease associated with consumers 'use of technology"*, Social influence was characterized as *"the extent to which consumers perceive that important others (e.g., family and friends) believe they should use a particular technology",* and Facilitating Conditions as the *"consumers' perceptions of the resources and support available to perform a behaviour"* (Venkatesh et al., 2012). Also, the moderator voluntariness was excluded, as it was considered specific for employee acceptance, alongside with a new relationship: the influence of Facilitating conditions

in behavioural intention was included. The variables added by the authors (Venkatesh et al., 2012) were Hedonic motivation, price and Habit, as observed in Figure 14 - Moderating effects in Performance Expectancy, Effort Expectancy, Social Influence and Facilitating Conditions, though not represented in the this figure, are the same as in its predecessor UTAUT model (Figure 13).

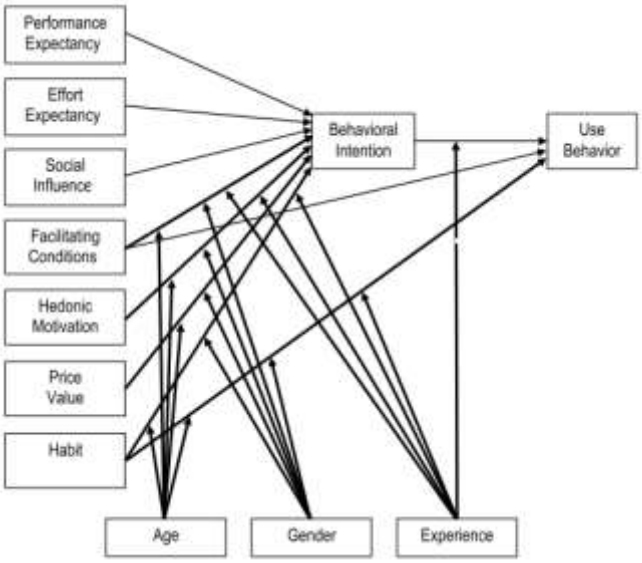

Figure 14: UTAUT 2, from Venkatesh et al., 2012; (Adapted from: ibid.)

As research shows, mostly through social psychology models, the field of IS, more specifically in the HCI area, has made substantial findings in the understanding and in the improvement of human interaction with computer-based technologies: about how people see and think of computer-based technologies, about human constraints on interaction with machines, about the factors that improve usage, and about the most relevant effects of technology on people and organizations (Kiesler & Hinds, 2004).

This work was extremely important to HRI and according to Yanco & Drury (2002), this research field can be viewed as a subset of the HCI, since robots might be perceived as IS. Hence, most of the work done in the HCI field can be adapted to be applied on HRI, if the complex, dynamic, and autonomous nature of robots is taken under consideration (Yanco et al., 2004). However, HCI literature offers few information in some specific and crucial HRI problems, such as the robot's embodiment and physical presence and the attitudes and beliefs towards robots (Huang, 2016). Over the last years, accompanying the evolution of robotics, there has been an enormous increase on publications regarding the acceptance of social robots. Therefore, a review of the most recently published literature is performed in the next section, to determine the most appropriate methodologies for this study, by evaluating which are the methodologies that are being used to address this challenge.

2.3.2. Social Robot Acceptance Studies

Regarding most of the available literature that focuses directly in the factors that influence the acceptance of social robots, there are mainly two different approaches. Some researchers ought to present qualitative analysis of the variables that were found most influential (Broadbent et al., 2009; Klamer & Ben Allouch, 2010; Young et al., 2008), while others (Fridin & Belokopytov, 2014;

Giger & Piçarra, 2018; Graaf et al., 2017; Heerink et al., 2010; Shin & Choo, 2011) added the development of acceptance models, adapted from prior technology acceptance models literature, that incorporate the specific variables regarding social robots that were found and the respective influences between such variables (see Table 16 Appendix A). Most models were evaluated in experiments with real robots (see Table 17 of Appendix B) followed by a questionnaire or simply through questionnaire. For testing, some (*e.g.* Giger & Piçarra, 2018; Graaf et al., 2017; Heerink et al., 2010; Shin & Choo, 2011) make use of the Structural Equation Modelling (SEM) (see more in Ullman & Bentler, 2013), while others (*e.g.* Fridin & Belokopytov, 2014; Graaf & Ben Allouch, 2013) resorted to other statistical methods such as correlation and regression analyses.

Starting with qualitative analysis studies, in Young et al. (2008), the aim of the study is to set guidelines for future domestic robot developers and designers, as an attempt on understanding how people respond to domestic robots, and on explaining their responsive behaviours. In this study, only two domestic robot types were taken under consideration: an existing task-focused robot and a more complex one, still in the prototype stage, being Roomba and RIKEN RI-MAN the respective examples (see Table 17 of Appendix B). The authors suggest several variables that were found to be the most influencing when considering domestic robot acceptance. These variables, in turn, are the results of a qualitative research in technology acceptance models, more specifically, the previously mentioned TRA, TPB and TAM and the Model of acceptance of technology in households (MATH), which were directly applied to HRI.

The suggested variables were separated in two categories, the first addresses to variables that directly impact how domestic robots are perceived by humans - Influencing Variables of Acceptance, which include Safety, Accessibility and Usability, Practical Benefits, Fun, Social Pressures, Status Gain and Social Intelligence. The second category reports to the variables that influence such perception - Perception Variables, including Previous Experience, Media and Personal Social Network.

In another example of qualitative studies, Broadbent et al. (2009), considers SAR for the elderly. In this study, the author presents an extensive research on how elders react and respond to this type of robot, highlighting the discovered influencing variables of such reactions and responses. This review includes the analysis of eleven robots, either built or used for healthcare purpose. Some of these robots already commercialized, though, most of them were still prototypes. In turn, the analysis is subdivided into three categories: robots that offer physical assistance, safety/monitoring robots and communication/companion robots. The influencing variables for the acceptance of this type of robots that were found were separated in two fronts: Individual Variables and Robot Variables. The first category addresses to the users and includes Age, Needs, Gender, Experience with Technology, Culture, Role, and Cognitive Ability and Education. The second, reports to the robots, and includes such variables as Appearance, Humanness, Facial Dimensions and Expressions, Size, Gender, Personality and Adaptability. Thereafter, the authors make some suggestions for the development of robots and for future research in this acceptance issue, such as: which measures should be applied when investigating these systems' acceptance, what should the robot's design specifications be, how personification

and customization of the robot's features, by their users, influence its acceptance and how changes in the expectations that humans have of social robots affects the acceptance of such systems, as adapting expectations to the robot's capabilities may increase its acceptance by users.

With the objectives of analysing relationship-building between the elderly and healthcare animal-like social robots, also providing insight on how elder users perceive these social robots for aging in place, *i.e.,* in the users homes, Klamer & Ben Allouch (2010) performed a field trial. This experiment was performed with three participants, all female, aged 50, 60 and 65, who lived in their households with the rabbit-shaped robot Nabaztag (see Table 17 of Appendix B) for 10 days. After this period, the participants underwent a questionnaire regarding their experience with the robot. The questionnaire was based on influencing factors for the acceptance and use of social robots, and for building and preserving a relationship with the robot. The first were considered in four fronts: Utilitarian Factors, provided by the TAM, Hedonic Factors, Social Factors and Personal Interest in Technology, while the second was mainly measured on whether the users perceived the robot as a machine or as a living creature and whether the users talked more to the robot or more about the robot. As a result, the questionnaire includes five topics, each containing the influencing factors related to them: General Use of Nabaztag, includes Intention to Use, Usefulness, Usage, Expectations, Health Exercises and Usefulness of Design. Communication involves Perceived Enjoyment and Perceived Playfulness. Relationship Development with Nabaztag accounts for Trust, Likeability, Source Credibility, Appearance and Novelty Effect. Social factors are divided in Subjective Norm and Self-Identity. The last only accounts for itself, *i.e.*, Personal Interest in Technology.

Results did not observe any improvements in users' health and participants did not find Utility in using the robot. Nonetheless, the robot was considered easy to use overall, yet, with some technical or usage problems. Also, Hedonic Factors were not found to influence acceptance of this social robot, in fact, they might only influence the development of human-robot relationship. Notwithstanding these results, all three participants manifested they wanted to make use of Nabaztag for following studies.

The Almere model was one of the first social robot acceptance models tested with SEM (Graaf et al., 2017), and was developed to evaluate the acceptance of SAR by the elderly. The model was developed by Heerink et al. (2010) and is based on the UTAUT with a few additional constructs specific to social robots. The model was tested with SEM, with data gathered from four different studies taking place at care homes and users' households where participants interacted with 3 different social systems (see Table 17 of Appendix B). Even though all experiments were different in almost every aspect, they all involved interaction with a technological social system and used the same questionnaire. The model consists in 13 constructs and 7 hypotheses. The constructs include Use, Intention to Use, Facilitating Conditions, Social Influence, Attitude Towards Use, PU and PEOU, Perceived Enjoyment, Perceived Adaptivity, Anxiety, Social Presence, Perceived Sociability and Trust. The suggested hypothesis represent which constructs are dependent of/determined by other constructs, therefore they address to the determinants of

Use, Intention to Use, PU, PEOU, Perceived Enjoyment, Perceived Sociability and Social Presence, which can be observed in Figure 15.

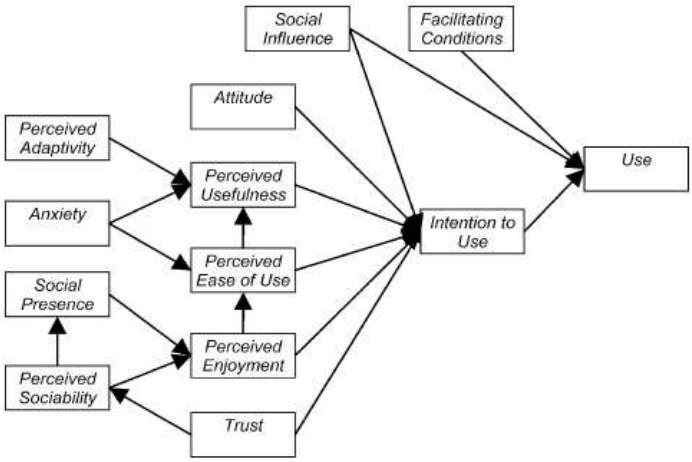

Figure 15: The Almere Model, from Heerink et al. 2010 (Source: *ibid*.)

The first experiment resorted to the iCat robot and focused on exploring the effects that the robot's social skills have. The experiment consisted on evaluating two different scenarios, one where the robot functioned autonomously with minor social skills and the other under a Wizzard of Ozz experiment, where the robot's social skills were controlled by an operator yet, perceived as autonomous to the users. The second reports to the evaluation of the influence that adaptiveness have, in this trial, a video of the RoboCare robot was shown to the participants. The third and fourth experiments are focused on the public and private usage of the systems, respectively. The third resorted to the iCat, but with a completely different approach than in the first. This time the robot was fully autonomous, and participants interacted with it through a touch screen. The last made use of Steffie, a virtual agent displayed on a screen, in this case, the interaction with the social agent was performed in a menu-based interface.

The model was sturdily supported, *i.e.*, all hypotheses were somewhat supported, except for the influence of Trust on Intention to Use. Results indicated a 59-79% explanatory power on the variance in Intention to Use and a 49-59% explanatory power in the variance of Actual Use.

Shin & Choo (2011) proposed another model, the "*socially interactive robots acceptance model*", which is an adaptation of the UTAUT/TAM. To build this model, the authors present a review about the acceptance behaviour of humans towards socially interactive robots, with the goal of finding which are the main variables that determine the users' Intention and Attitudes Towards the Use of these robots. Such variables include Social Presence (SP), Perceived Sociability (PS), Perceived Adaptability, PU, and Perceived Enjoyment, whose dependencies were given in ten hypotheses (H1 to H10), which can be observed in Figure 16.

The model was tested with the SEM and for data gathering, the author performed a field trial, followed by a questionnaire. In this study partook 210 participants, all under 51 years old, most of which were aged 21-30 (44%). The trial consisted in a demonstration, by an instructor, on how to interact with three different social robots Tito, PaPeRo and AIBO (see Table 17 of Appendix B), followed by a 20 to 30 minutes interaction with the robots.

The proposed hypothesis (H1 to H10) suggested in this model were all supported by the results, proving the influences of PU and PE in Intention to Use but not so much in Attitude Towards Use, which, in turn, was surprisingly mainly influenced by Social Presence. Also, the constructs PA and PS have been observed to determine Attitude. The fact that Social Presence turned out to be the most influencing variable for the acceptance of social robots, led the authors to suggest that social robots are different from other technologic systems as they are not perceived as objects, yet, they are perceived more as social agents.

To evaluate the acceptance of SAR in education, more specifically its acceptance by preschool and primary school teachers, Fridin & Belokopytov (2014) performed a field study. This study resorted to an adaptation of the Almere Model (Heerink et al., 2010) to the experiment set-up. This adaptation was made in order to fit the experiment, which consisted in the interaction of the NAO robot (see Table 17 of Appendix B) with people on a workshop. Out of 36 people that either interacted or observed interaction with the robot, only 18 completed the UTAUT questionnaire suggested in Heerink et al. (2009), which is the article regarding the first experiment considered in Heerink et al. (2010). Hence, the constructs Actual Use and PEOU were dropped, excluding the hypothesis respective to them.

The answers to the questionnaire were evaluated using other statistical methods, due to the lack of participants to perform the testing with SEM. The constructs' consistency was evaluated by determining the Cronbach's Alpha, while hypotheses were confirmed by a correlation analysis, followed by linear regression analysis.

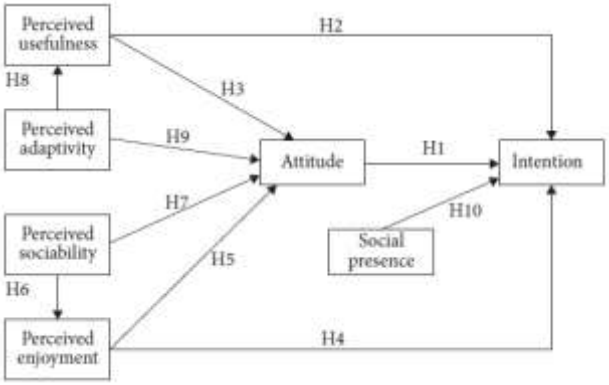

Figure 16: The socially interactive robots acceptance model, from Shin & Choo, 2011 (Source: ibid.)

Results indicated that the constructs facilitating conditions, social influence, social presence and trust, were not found reliable. Hence, only three hypotheses were tested, and all were confirmed, presenting good results especially in the influences of PU in Intention to Use and of Perceived sociability in Perceived Enjoyment.

In Graaf & Ben Allouch (2013) the authors present a summary of the variables that were found the most influencing in a four-fold approach. The study includes the theoretical justification of the chosen variables in their extensive analysis. The model accounts for four categories of variables, that are subdivided into (1) Attitudinal Beliefs, which include and the actual determinants of acceptance, *i.e.,* Attitude Towards Use, Use Intention and Actual Use, and Utilitarian and Hedonic Factors. The other categories are (2) Social Normative Beliefs, including Image and Social Influence, (3) Control Beliefs, regarding Anxiety Towards Robots and Robot

Experience, among others, and (4) User Characteristics. This structure was mostly based on the TPB with additional variables that were found important throughout the performed literature review.

A field trial with 60 participants was performed with interaction between these participants and the robot NAO (see Table 17 of Appendix B), to evaluate the reliability of the influencing variables for the acceptance of social robots that were found in the literature review. Results of this experiment suggested major influence of the variables Usefulness, Adaptability, Enjoyment, Sociability, Companionship and Perceived Behavioural Control in the acceptance of social robots.

Following this study, Graaf et al. (2017), presented a conceptual model for social robot acceptance in domestic environments, tested with SEM, what was not possible in the previous study due to the sample dimension. As the latter, this model is based on the TPB, with the objective of extending the TBP to the specific nature of social robots. Hence, specific constructs, respective to social robots with a robust theoretical background are incorporated as determinants of the actual TPB variables: Attitudinal Beliefs, Normative Beliefs and Control Beliefs.

Attitudinal Beliefs refer to the user's perceived behaviour when using a social robot in the future and is divided in Utilitarian Factors, which include Usefulness, Ease of Use, Adaptability and Perceived Intelligence, and Hedonic Factors. Addressing for Perceived Intelligence, Enjoyment, Attractiveness, Animacy, Sociability, Companionship and Social Presence. Normative Beliefs consist in the user's assessment of the main norms concerning the usage of a social robot, this being subdivided in Social Normative and Personal Normative constructs. The first accounting for Social Influence and Status, and the latter including privacy, Trust and Societal Impact. Control Beliefs are perceived as the circumstantial variables that affect the use of a social robot, which accounts the variables of Self-Efficacy, Safety, Anxiety Towards Robots, Personal Innovativeness and Cost. The influences between the constructs were presented in 14 hypotheses, displayed in Figure 17 from H1 to H14.

The model was tested with SEM, with data gathered in the Netherlands, from 1168 valid questionnaire responses. Results suggested that the most influencing factors for the acceptance of social robots are Utility and Usefulness. Also, the influences of Hedonic Factors and Control Beliefs in Utilitarian Factors were verified, as well as the influence of Hedonic Factors in Control Beliefs. Nonetheless, the influences of Normative Beliefs were not observed. In addition to this, and in line with the results from Graaf et al. (2014), it was noted that early adoption is mostly influenced by Control Beliefs, while continuous actual use is majorly determined by Attitudinal Beliefs. Moreover, the Sociability and Companionship of social robots was predominantly judged as negative. Furthermore, with participants not finding these robots useful, and even preferring other technologies that fulfil the same needs. To that extent, the authors emphasise the need for developers to clearly express the applicability of the robot and to build robots that are more useful, easy and pleasant to use. However, the proposed model revealed serious problems in the second-order measurement model, leading the researchers to evaluate the influence of each and every variable that was included in the Attitudinal Beliefs.

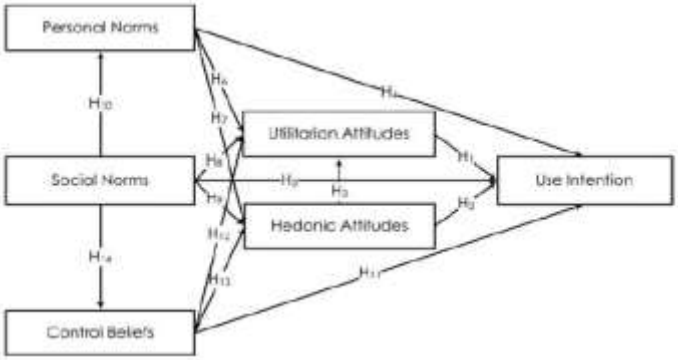

Figure 17: Model of Domestic Social Robot Acceptance, from Graaf et al., 2017 (Source: ibid.)

Giger & Piçarra (2018) developed a social robot acceptance study in the workplace context. The authors employed and adapted the Model of Goal Directed Behaviour (MGB) (Perugini & Bagozzi, 2001), to evaluate how the robot factors: Perceived Warmth, Perceived Competence and its appearance, affect the components of the model, possibly influencing intention to work with a social robot (acceptance). Figure 18 displays both the MGB and the Model and the "Background factors" used in this study.

The MGB combines the TPB with the Theory of Self-Regulation in a way that attempts to complete the TPB's limitations (lack of emotional and motivational aspects), by including the variables: Anticipated Emotions (Positive or Negative) and Behavioural Desire. This model accounts for the variables: frequency of past behaviours, recency of past behaviour, Behavioural Intention and Perceived Behavioural Control, as the determinants of a certain behaviour. In turn, Behavioural Intention is determined by Behavioural Desire, *i.e.,* "what one wants to do or to *achieve*", and frequency of past behaviour. Behavioural Desire "*plays a key mediational role, because it is assumed to transform reasons to perform a given behaviour into a motivational drive to do so*" (Giger & Piçarra, 2018), and is, therefore, determined by: the already known variables: Attitude Towards Use, Subjective Norm and Perceived Behavioural Control, and by Frequency of Past Behaviour and Anticipated Emotions (Positive or Negative), *i.e.,* the perceived feelings that a certain behaviour elicit on an individual (Perugini & Bagozzi, 2001). For this particular study, the variables Frequency of Past Behaviour and Recency of Behaviour were excluded, which is depicted in Figure 18 by dashed lines.

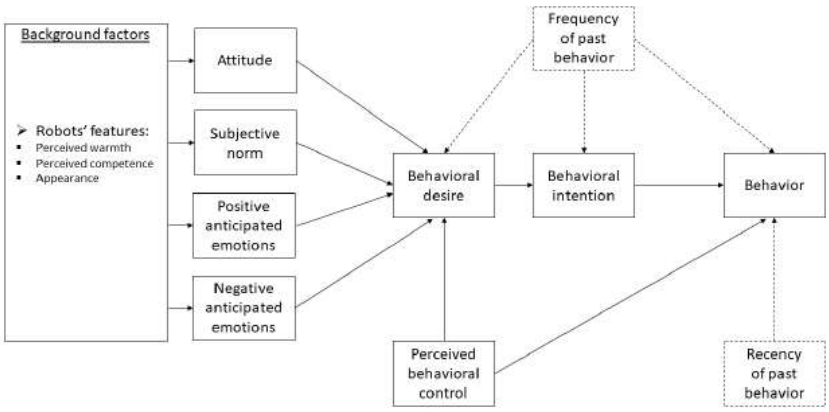

Figure 18: Model of Goal-Directed Behaviour, from Perugini & Bagozzi, 2001 (Source: Giger & Piçarra, 2018)

This work aims at exploring the roles that the robots' Perceived Warmth and Perceived Competence, as functions of the robot's appearance, have on Intention to Work with social robots. As mentioned in this article and citing Fiske et al., (2007), Perceived Warmth addresses to the "*traits that are related to perceived intent, including friendliness, helpfulness, sincerity, trustworthiness and morality*", while Perceived Competence refers to the "*traits that are related to perceived ability, including intelligence, skill, creativity and efficacy*". In addition to this, the roles that the variables Behavioural Desire and Anticipated Emotions have in the prediction of Intention to Work with social robots were also analysed by a comparison of three models: the TPB, the TPB with the variable behavioural desire and the MGB.

To test these models, the authors resorted to PLS-SEM, for which 217 participants partook in an experiment that resorted to three robots: SnackBot (Machinelike), Asimo (Humanoid) and Actroid DER1 (Humanlike) - see Table 17 of Appendix B). Participants were randomly assigned to one of these robots, which was presented in a short video, followed by a questionnaire.

This study concluded that the MGB presented good explained variance of Intention to Work with Social Robots, verifying the that Behavioural Desire and Anticipated Emotions play an important role in this explained variance. In turn, the effects of Perceived Warmth and Perceived Competence in intention were also noticed, while effect of the robot's appearance was not confirmed.

2.3.3. Review of acceptance studies Summary

More recently, the research's focus on social robotics has had an astonishing growth. This might be due to the applicability of such systems, as observed in Section 2.2.2. Notwithstanding, social interaction between humans and robots is still quite limited and predictable, leading to low acceptance rates in general, especially on the long-term interactions, beyond the novelty effect.

Therefore, to increase the acceptance of social robotics, it is essential to perform user-centred studies. It is by including potential users at an early stage of the development, which will shape future design and features to the "needs" and "wants" of these potential users, that their expectations and needs are more easily met (Graaf et al., 2017).

Acceptance of technology has already been researched in the fields of IS and HCI. Many studies have brought to us prominent technology acceptance models and theories. Most of these theories are based on social psychology models (predominantly TRA and TPB), which are considered to be well-researched, successful tools for predicting and explaining specific behaviours in several research fields. Such social psychology models have found how intention can be a good determinant of certain behaviours. Others were developed with a background on other technology acceptance models, such as the UTAUT, which aggregates the best influencing variables of acceptance among eight other technology acceptance models and theories.

Following the research fields of prior technology acceptance such as IS, in the field of social robot acceptance, researchers have presented several acceptance explorative studies, concept models and theories (Broadbent et al., 2009; Fridin & Belokopytov, 2014; Giger & Piçarra,

2018; Graaf & Ben Allouch, 2013; Graaf et al., 2017; Heerink et al., 2010; Klamer & Ben Allouch, 2010; Shin & Choo, 2011; Young et al., 2008).

As previously mentioned, Intention towards a certain behaviour has been found to be a good determinant of that particular behaviour. Therefore, in social robot acceptance models, and considering Use as the variable that better explains acceptance, Intention to Use is considered the main influencing variable of Use (Heerink et al., 2010). Use is a variable that is very hard to measure in short-term studies, hence, and assuming it is mainly determined by Intention to Use, most models do not even include this variable (Fridin & Belokopytov, 2014; Giger & Piçarra, 2018; Graaf et al., 2017; Shin & Choo, 2011). Even though the reviewed work approached different application fields (domestic, healthcare and therapy, SARs for the Elderly, education and workplace) and different models in which they are based upon (TPB, TAM, UTAUT, MGB), there was observed some convergence among the results found. The variables Usefulness, Ease of Use, Adaptability, Enjoyment, Sociability and Social Presence were considered the most influencing variables in the acceptance of social robotics (Fridin & Belokopytov, 2014; Graaf & Ben Allouch, 2013; Graaf et al., 2017; Heerink et al., 2010; Shin & Choo, 2011). To achieve such results, the reliability and robustness of the constructs and the hypothesized influences among constructs were tested. Most studies have performed HRI experiments with potential users and social robots (*e.g.* Heerink et al., 2010; Shin & Choo, 2011) or with video representation of robots (*e.g.* Giger & Piçarra, 2018), where participants after these experiments answered a questionnaire. Most models were tested with SEM (see more in Ullman & Bentler, 2013), while others resorted to other statistical methods, essentially due to the lack of participants to apply SEM.

Other deductions highlight that, to possibly increase the acceptance of social robots by humans, the acceptance measures and guidelines should be reinforced and clearly defined (Broadbent et al., 2009), and the robot's purpose must be clearly defined and expectations must be met, even if they need to lowered (Broadbent et al., 2009; Graaf et al., 2017).

2.4. Literature Review Conclusions

Having summarized the robotic evolution towards social robots and briefly analysed the market of robotics in Section 2.1., defined and characterized social robots and its application fields in Section 2.2. and reviewed the methodologies being applied to evaluate the acceptance of these systems in Section 2.3., this Section 2.4. outlines the main conclusions of the literature review performed.

As the world of robotics is evolving towards intelligent systems, and robots are able to perform a vast range of tasks, either physical or cognitive, these systems are starting to become ubiquitous in our society. From drones and autonomous vacuum cleaning robots to autonomous cars, from logistics to medical robots, among many other types, it is clear that robotic systems are now part of our society.

Such evolution of robotics, led to the development of social robots, *i.e., "robots that elicit social responses from their human users because they follow the rules of behaviour expected by*

their human users". (Graaf et al., 2016). The main application fields of these robots are Health Care and Therapy, Education, Domestic and Workplace and Public Spaces, as observed throughout Section 2.2.2.

One of the main challenges inherent to these robots is its acceptance by humans, as the mere presence of these systems does not increase people's acceptance and willingness to interact (Graaf & Ben Allouch, 2015). Also, the cognitive capabilities of most of the existing systems are quite limited, leading to low acceptance, especially after the novelty effect when these robots' behaviour becomes increasingly more predictable. 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. Also, due to the complexity of these systems, their affordability is very limited to personal users, which englobes social robots for domestic and healthcare and therapy (e.g. for aging in place), though it is not for organizations, companies, governments, which include Education, Workplace and Public Spaces. 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 for 2017-2020.

Following this train of thought, it is argued that the introduction of social robots in our society starts by employing social robots in Public Spaces, where engagement and acceptance rates are the highest when compared to other application fields and organizations are able to afford such technologies. 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. Furthermore, this introduction of social robotics in Public Spaces appears to be happening 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.

As observed throughout Section 2.3.1., 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, especially the UTAUT, expressing more explained variance than the other two, though the difference is not that significant. Therefore, it cannot be said which one is the best to use as a basis for the development of a conceptual model for the acceptance of social robots in public spaces. Also, all these models have been successfully applied to predict technology acceptance and, used as a basis in social robot acceptance models (Giger & Piçarra, 2018; Heerink et al., 2010; Shin & Choo, 2011). However, while the TPB and the TAM were developed with its roots on the TRA, with strong theoretical foundations, the UTAUT was built by combining the most significant variables of eight other technology acceptance models, consequently leading to extremely good results. When comparing these models in terms of difficulty of application, while the TAM and the

UTAUT have standardized measures, in the TPB, the measures are built specifically for each different context in which it is applied. As the objective is to build a model that comprises all the variables that were found the most influencing of social robot acceptance, throughout the literature review, the UTAUT2 was selected as a basis for the development of a conceptual model for social robot acceptance in public spaces. 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 throughout Section 2.3.2. (usefulness, ease of use, adaptability, enjoyment, sociability and social presence). Thus, as the extended version of the UTAUT, the UTAUT2 includes most of the aforementioned variables, only lacking on sociability and social presence - variables specific to the essence of social robots. It was the one that best expressed the theoretical findings.

Moreover, there is a very scarce number of studies in this context and, as observed throughout Section 2.3.2., there 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, based on extending the UTUAT2, 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, where, based on the literature review, a conceptual acceptance model, tested with the SEM, has never been applied.

The next chapter focuses on detailing the proposed acceptance model and the procedure performed for data gathering, closing with a description of the statistical techniques used for the model analysis.

3. Methodology

This chapter focuses on detailing every aspect of the work performed to develop and analyse a conceptual model for social robot acceptance in public spaces. Thus, the first section addresses to the development of this model, by describing each of its constructs, the relations between them, and the measures used for each construct, *i.e.,* the measurement model.

The second section of this chapter describes how the questionnaire, derived from the measurement model, was built. It starts by detailing all the material used in the questionnaire. Afterwards, it describes all the procedures required to present a final version of the questionnaire.

Finally, the methodology to be used in the result analysis of the conceptual model will be outlined, detailing every step that will be performed, alongside the theoretical aspects of the methods used, especially the statistical method PLS-SEM, in the data analysis for the model testing.

3.1. Model for Social Robot Acceptance in Public Spaces

The conceptual model proposed in this study, is based on the extended version of the UTAUT, the UTAUT2, and comprises the variables that were found the most influencing for the acceptance

of social robots throughout Section 2.3.2. (usefulness, ease of use, adaptability, enjoyment, sociability and social presence). As the UTAUT, the UTAUT2 has also shown great explanation power and has been confirmed to be well-established, especially in recently developed, innovative information systems (C. Y. Huang & Kao, 2015). It proposed an extension of this model, by adding two dimensions specific to social robots, *i.e.*, sociability and social presence.

As observed previously in Section 2.3.1., the UTAUT 2 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. 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.

3.1.1. Model Constructs

Performance Expectancy (PE)

As previously mentioned, Performance Expectancy is defined as "*the degree to which using a technology will provide benefits to consumers in performing certain activities",* which is, essentially, based on the TAM's usefulness, in turn, referred to as: a person's belief that using the system will improve his/her performance (Davis et al., 1989). This variable has not only been shown critical to social robot acceptance, as seen throughout Section 2.3.2., but has also been considered to be influential in HRI studies in public places such as drone acceptance (Ramadan et al., 2016; Zhang, Liang, & Yue, 2015), non-anthropomorphic robot acceptance (May et al., 2017), and in social robot acceptance in public spaces (Kanda et al., 2009; Weiss et al., 2008, 2015). Alongside with usefulness, the variable adaptability, is comprised within Performance Expectancy, as it has been found to be a direct determinant of usefulness in social robot acceptance studies (Heerink et al., 2010; Shin & Choo, 2011). Adaptability denotes to an individual's evaluation of the robot's behaviour to be adaptive in an unstructured environment and to one's needs (Graaf & Ben Allouch, 2013), which is a fundamental characteristic for a social robot to successfully perform in public spaces (Leite et al., 2013), and has been shown to influence its acceptance in such environments (Weiss et al., 2015).

Effort Expectancy (EE)

This variable derived essentially from TAM's ease of use, and is described as "*the degree of ease associated with consumers 'use of technology"* (Venkatesh et al., 2003), in turn, ease of use refers to the lack of effort the usage of the system may provide to the user (Davis et al., 1989), which are basically the same concept. Furthermore, ease of use has been considered to be an influential variable for social robot acceptance, as observed in Section 2.3.2. and HRI studies in public places such as drone acceptance (Ramadan et al., 2016; Zhang et al., 2015), non-anthropomorphic robot acceptance (May et al., 2017), and also in social robot acceptance in public spaces (Kanda et al., 2009; Weiss et al., 2008, 2015).

Social Norms (SN)

As previously mentioned in Section 2.3.1., the construct social influence was developed based on the constructs: subjective norm, social factors and image. However, the indicators used to measure this construct do not reflect the concept of status/image and thus, this elicited a change in the construct. Therefore, instead of resorting only to the variable social influence, it seemed more complete to consider Social Norms (SN), which comprises social influence and status/image, as did Graaf et al. (2017). SN are defined as "*an individual's beliefs regarding the likelihood and importance of the social consequences of performing a particular behaviour"* and was suggested to be composed of the following variables: Social Influence and Status (Graaf et al., 2017). The first refers to an individual's thoughts of how important people to him and other people will perceive his use of a social robot, while the second regards an individual's assumption that the use of a social robot will increase his image/status (Graaf et al., 2017). These variables have shown to be a motivational aspect for the adoption of innovative technologies, which social robots can be considered (Graaf & Ben Allouch, 2013). In addition to this, Social Norms have also been considered as influential in the context of public spaces (Weiss et al., 2008).

Facilitating Conditions (FC)

Facilitating conditions is described as the *"consumers' perceptions of the resources and support available to perform a behaviour"* (Venkatesh, et al., 2012) and is usually conceptualized as Perceived Behaviour Control, which is describes as *"the perceived ease or difficulty of performing the behaviour, perception of internal and external constraints on behaviour",* in Giger & Piçarra (2018). In public spaces, social robots are expected to be deployed by organizations to be used by the general public, thus, they are assumed to be at the disposal of the users. Hence, the availability of resources or external constraints are neglectable, and this variable is assumed to be especially determined to self-efficacy. The variable self-efficacy refers to an individual's perceived skills to use a social robot and has been shown to be a crucial variable for the acceptance of social robots, not only according to the models in Graaf et al. (2017) and in Heerink et al.(2010), but also in the user acceptance studies in public spaces Weiss et al. (2008, 2015).

Hedonic Motivation (HM)

Hedonic Motivation 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. It is often conceptualized as enjoyment in technology and social robot acceptance studies and refers to the sensations of fun or pleasure withdrawn from the usage of a social robot (Heerink et al., 2010; Venkatesh et al., 2012). This variable was added to the UTAUT as it was considered to be a determinant of usage intention and behaviour of technology, and consequently, technology acceptance by consumers. Furthermore, enjoyment has been shown to be a crucial variable not only for social robot acceptance in general, (Graaf & Ben Allouch, 2013; Heerink et al., 2010; Shin & Choo, 2011) but also, in a urban context, both in HRI studies (May et al., 2017; Ramadan et al., 2016) and in social robot acceptance studies (Kanda et al., 2009; Weiss et al., 2008, 2015).

Sociability (SB)

Social robots are developed to socially interact with humans, and thus are required to have the necessary social skills to do so. Research shows that a the more social a robot is, the more adequate is its communication with users, consequently performing better, and in an easier and more enjoyable way (Graaf & Ben Allouch, 2013; Heerink et al., 2010; Shin & Choo, 2011). Also, the more social skills a robot presents, the more naturally it is perceived as a social entity (Graaf & Ben Allouch, 2013). Heerink et al. (2010) were the first to include this variable in a social robot acceptance model and explore its role in the acceptance of these systems. Findings observed a correlation between sociability and all the UTAUT variables, proving its importance and direct influence on intention to use social robots, and consequently in their acceptance by humans. In light with this work, Shin & Choo (2011), also included this variable in their model of socially interactive robot acceptance. The variable was considered to arise from the concept of social intelligence of a robot, *i.e.,* the perception of the robot's social skills by their users. Results were similar to the aforementioned study, verifying its importance in the acceptance of social robots by humans. More recently, Graaf et al., (2017) also included sociability in their social robot acceptance model, as one of the variables determining of hedonic attitudes. Despite the problems that the second order measurement brought, as discussed previously, sociability was one of the only variables that was partially verified as direct determinant of use intention of social robots. In this study, in light with the ones previously mentioned, sociability was added to this extended version of the UTAUT2, specific to social robots. Sociability relates to an individual's perception of the robot's level of communicative, emotive and cognitive skills, as well as of its social behaviour in terms of social norms (Graaf & Ben Allouch, 2013). Thus, it can be observed that this variable is essential to a successful human-social robot interaction in general (Graaf & Ben Allouch, 2013; Graaf et al., 2017; Heerink et al., 2010; Shin & Choo, 2011) and also in the context of the present study, *i.e.,* public spaces (Mirnig et al., 2012; Weiss et al., 2008, 2015).

Social Presence (SP)

Social robots are embodied systems able to interact in a social way, using verbal and non-verbal behaviours that follow societal norms designed by their developers, in order to elicit social responses from humans (Graaf et al., 2017; Heerink et al., 2010). This way, it is common for individuals to perceive these robots as social agents, *i.e.,* to anthropomorphise them. Anthropomorphism is described as the propensity of giving human features to material objects, consequently rationalizing their behaviours, and is mostly prompted by social presence (Graaf et al., 2017). Social presence is defined as "*the experience of sensing a social entity when interacting with the system"* (Heerink et al., 2010), and has been considered one the most influencing variables, specific to social robots, of their acceptance by humans, as it has been previously mentioned in Section 2.3.2., in Fridin & Belokopytov (2014), Graaf & Ben Allouch (2013), Graaf et al. (2017), Heerink et al. (2010) and Shin & Choo (2011). In addition to this, social presence was found to be a key variable for the acceptance of social robots in urban environments, *i.e.,* public places (Mirnig et al., 2012; Weiss et al., 2008, 2015). Based on this literature, it is projected that social presence will be a direct determinant of intention to use social robots in public spaces. Thus, by including this variable in the UTAUT2 model, it is expected, not only to evaluate its results, but also provide a more complete extended version of the UTAUT2 specific to social robots.

From now on, the all the dimensions of the model will be addressed by their acronyms, thus, Use Intention is UI, Performance Expectancy is PE, Effort Expectancy is EE, Social Norms is SN, Facilitating Conditions is referred as FC, Hedonic Motivation is HM, while Sociability is SB and Social Present is addresses as SP.

3.1.2. Model Hypotheses

The model that is proposed in this study derives from the UTAUT2 presented by Venkatesh et al. (2012), only with UI as the outcome variable. Thus, all the variables kept, *i.e.,* PE (as Usefulness and Adaptability), EE (as Ease of Use), SN (as social influence and image), FC (as Perceived Behavioural Control), HM (as Enjoyment) with the justified exclusion of Habit and Cost, were assumed, as in the original design, to be direct determinants of UI. In addition to this, it was paramount to include the most influencing variables of social robot acceptance by humans, withdrawn from the literature in Section 2.3.2. While the variable usefulness, ease of use, adaptability and enjoyment were already included in the UTATUT2, sociability and social presence were not, which led to the development of a new model that also comprised these variables. The inclusion of sociability and social presence in this model attempts to provide an acceptance model specific for social robots, that assumes these variables as direct determinants of UI of such systems. This model, as in the UTAUT2, also includes the moderating variable age, gender and previous robot experience, which will be used to explore whether there are differences in the path coefficients of the model. Therefore, this model assumes the following hypotheses, also displayed in Figure 19 (the arrows from each moderating variables to each of the models hypothesis are not represented, allowing for a better visualization of the model):

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.

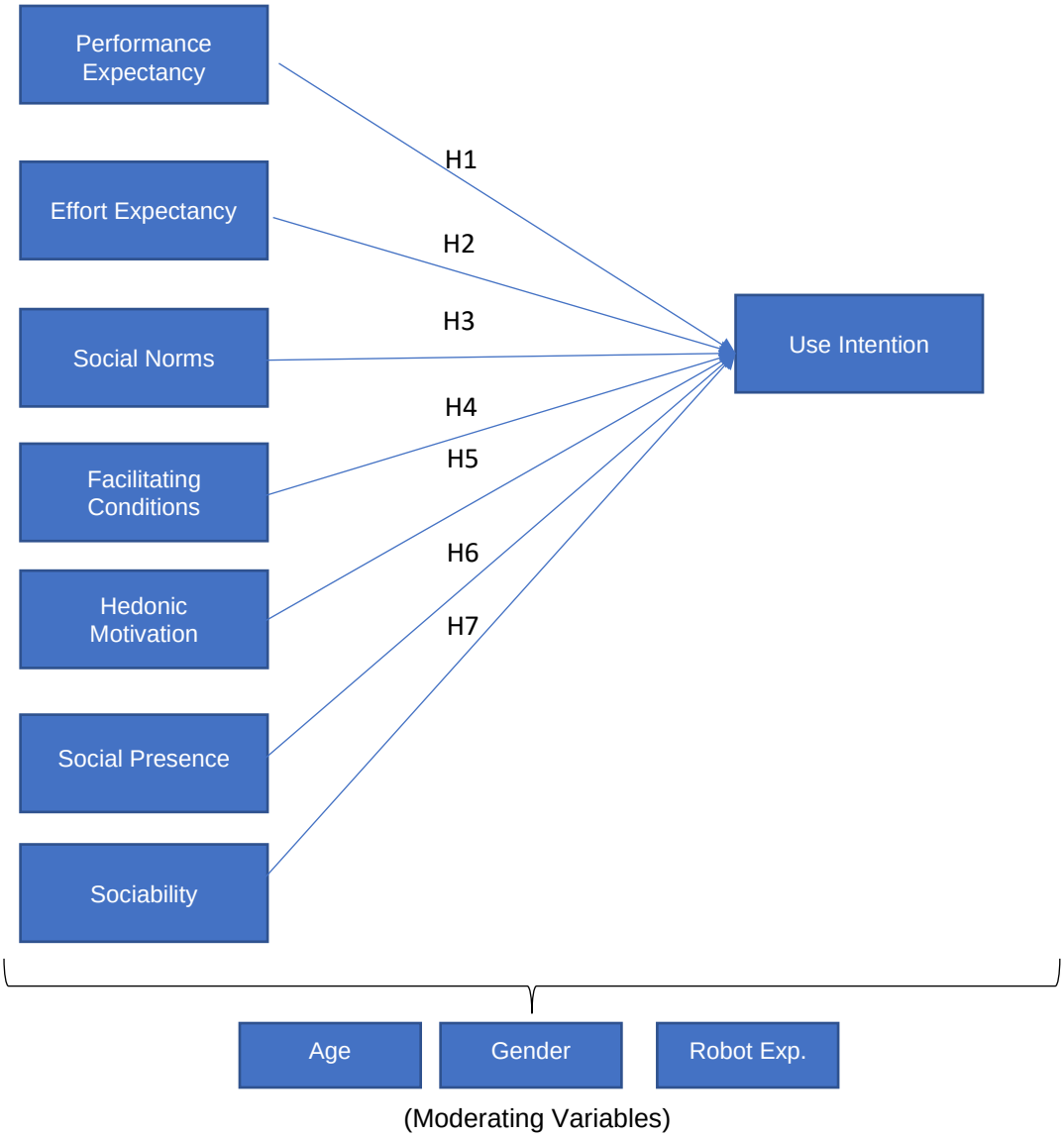

Figure 19: Conceptual model for social robot acceptance by humans in public spaces.

3.1.3. Measurement Model

In order to estimate any conceptual model, one has to measure the variables in these models, and only then, analyse the relations between these variables or constructs. These constructs can be very objective as age or gender, though, mostly these constructs are complex concepts, such as the constructs in this study - Section 3.1.1. To measure similar constructs, previous studies mostly used Likert scales for the items/indicators (Graaf et al., 2017; Heerink, 2010). Thus, for this study a 7-point Likert scale was chosen to measure each indicator. The Indicators/items derive from the literature and were rigorously adapted from the context of social robots in other fields to the context of social robots in public spaces. Also, as this study was performed in Portugal, all the items were translated to Portuguese.

The outcome variable (Endogenous Variable) in this conceptual model is UI, to measure this variable, a scale withdrawn from Graaf et al. (2017), which derived from Moon & Kim (2001), was used as a baseline. PE was measured with items from usefulness and adaptability. The measures used for the variables usefulness and adaptability were withdrawn from Heerink et al. (2010), alongside EE, which is based on the ease of use scale. For the Hedonic Motivation (HM), it was decided to use the variable enjoyment, which was measured based on the scale presented by Heerink et al. (2010). For Sociability (SB) and Social Presence (SP), the scales respective to these constructs presented by Heerink et al. (2010) were considered the most appropriate, and were used as the basis for the measurements used for these constructs. SN were measured with items from social influence and status, which were measured with the scales proposed in Graaf et al. (2017). 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), that resorted to an adaptation of the scale presented by Richetin & Perugini (2008).

In order to relieve the boredom and build a more solid measurement model of the survey as, according to Graaf et al. (2017), *"Incorporating fewer items in the questionnaire leads to a more parsimonious model and lowers the burden on the participants"*, some scales were reduced in size. The exclusion of items was performed mostly due to contextual adaptation to public spaces. Thus, this was performed in most of the constructs: usefulness, adaptability, ease of use, enjoyment, social presence, sociability, social influence, status and perceived behavioural control. The measurement scale chosen for PE is composed by a scale of usefulness and adaptability. From usefulness one item was removed as it did not explicitly relate to the usefulness of the robot and from the adaptability scale chosen, only two out of three items were kept as the one removed as it conflicted with the experiment of the present study. Two items were removed from the scale of perceived ease of use to measure EE, as they were considered to be more referent the FC, more specifically to the self-efficacy concept. The scale of enjoyment for HM comprised five items. One of these items was not considered relevant, as it required having a conversation with these robots. For social presence, two items were withdrawn, as they required real interaction with robots, which does not fit the procedure of this study. The same was for SB, as one item required

real interaction with robots, thus, only the other two items were kept. The scale chosen to measure social influence one item required to consider the purchase of these robots, what is not possible in the context of this study, thus explaining the removal of this item from the measurement scale. For the construct status, one item was excluded due to the requirement of "owning a robot", which is not possible for users in the context of public spaces. In the scale chosen for perceived behavioural control, one item was considered to be in conflict with the concept of ease of use and was, thus, removed.

When considering the measurement model of any expectation model, there are two types of indicators, *i.e.,* Reflective and Formative. In a reflective measurement the changes in the latent variable (measured construct), directly influence their respective indicators. On the other hand, in a formative measurement, changes in one or more indicators cause changes in the latent variable (measured construct). Therefore, in a reflective measure it is required highly correlated items. In addition, when representing a reflective measure, the arrows go from the latent variable to the indicators, while when representing a formative measure, the arrows go on the opposite direction, from the indicators to the latent variable. Having thus, characterized this difference, it can now be noted that all the indicators used in the measurement scales of the constructs of this model are reflective. Table 1 lists all the items selected for each of the constructs of this extended version of the UTAUT2 for social robot acceptance in public spaces, whilst, following this table, a representation of the this model is presented (Figure 20), now with the respective items.

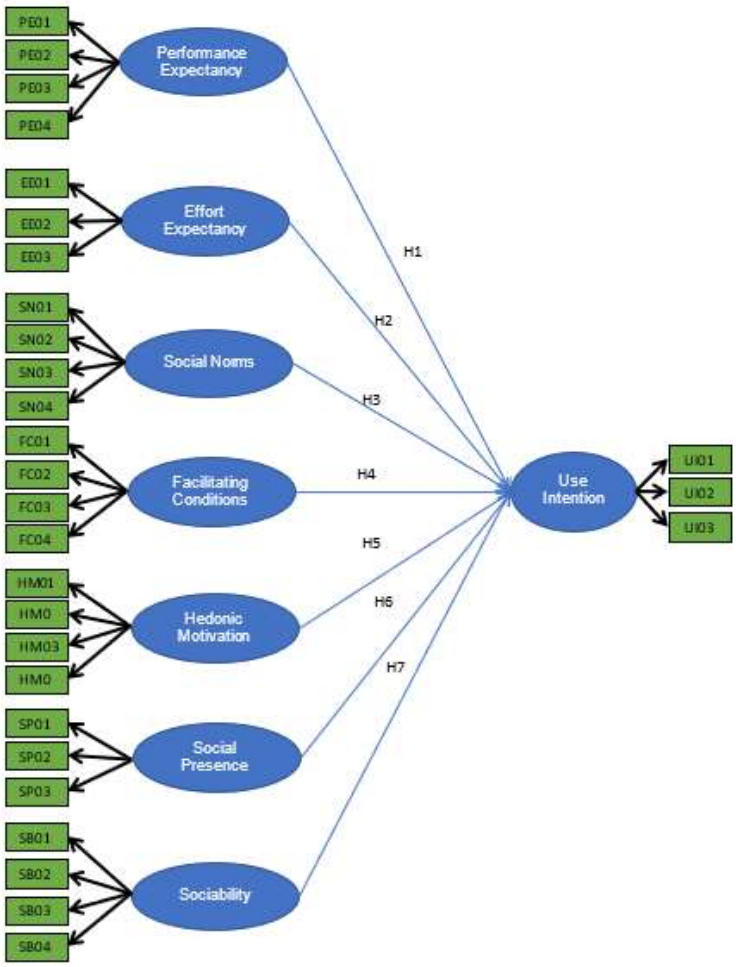

Figure 20: Conceptual for social robot acceptante in public spaces and its respective measurement model

Table 1: Items of the Measurement Model

Construct	Item#	Item	Source
Use Intention	**UI01**	**EN:** Assuming I have the opportunity to use these robots, I would use them on a regular basis in the future. **PT:** Se eu tiver a oportunidade de utilizar estes robôs, utilizá-los-ia frequentemente no futuro.	Moon & Kim (2001)
	UI02*	**EN**: Assuming I have the opportunity to use these robots, I will frequently use them in the future. **PT:** Se eu tiver a oportunidade de utilizar estes, irei utilizá-los regularmente no futuro.	
	UI02	**EN:** I'm willing to put an effort to use these robots. **PT:** Estou disposto a fazer um esforço para utilizar estes robôs.	Giger & Piçarra (2018)
	UI03	**EN**: I will strongly recommend others to use these robots. **PT:** Recomendo a utilização destes robôs a outras pessoas	
Performance Expectancy	**PE01**	**EN**: I think these robots are useful to me. **PT:** Considero estes robôs úteis para mim.	Heerink et al. (2010)
	PE02	**EN:** It would be convenient for me to have these robots at my disposal. **PT:** Seria conveniente para mim ter estes robôs ao meu dispor.	
	PE03	**EN:** I think these robots can be adaptive to what I need. **PT:** Considero que estes robôs se conseguem adaptar às minhas necessidades.	Heerink et al. (2010)
	PE04*(R)	**EN:** I think these robots will only do what I need at that particular moment. **PT:** Acho que estes robôs só farão o que eu preciso num momento específico.	
	PE04	**EN:** I think these robots help me accomplish things more quickly. **PT:** Considero que estes robôs me ajudam a realizar as tarefas mais rapidamente.	Venkatesh et al.(2012)
Effort Expectancy	**EE01**	**EN:** I think I will know quickly how to use these robots. **PT:** Considero que, rapidamente, saberia como utilizar estes robôs.	Heerink et al. (2010)
	EE02	**EN**: I find these robots easy to use. **PT**: Considero estes robôs fáceis de utilizar.	
	EE03	**EN**: I think I could use these robots without any help. **PT**: Penso que conseguiria utilizar este robô sem qualquer ajuda.	
	EE04**	**EN**: I think I can use these robots if there is someone around to help me. **PT:** Penso que conseguiria usar estes robôs se alguém me ajudasse.	
Social Norms	**SN01**	**EN**: People will find it interesting to use these robots. **PT:** As pessoas irão achar a utilização destes robôs interessante.	Lee, et al. (2006)
	SN02	**EN**: People will find these robots attractive. **PT:** Penso que as pessoas irão achar estes robôs atrativos.	
	SN03	**EN**: People who use these robots have more prestige than those who do not. **PT:** As pessoas que utilizam estes robôs têm maior prestígio do que as que não o fazem.	Venkatesh & Davis (2000)
	SN04	**EN**: People who use these robots have a higher profile than those who do not. **PT:** As pessoas que utilizam estes robôs social têm um estatuto mais elevado do que aquelas que não o fazem**.**	
Facilitating Conditions	**FC01**	**EN**: I would be able to use these robots. **PT:** Sinto-me apto para utilizar estes robôs.	Giger & Piçarra (2018); Richetin & Perugini (2008)
	FC02	**EN**: I'm confident that I have the knowledge to be able to use these robots. **PT:** Estou confiante que tenho as capacidades necessárias para utilizar estes robôs.	
	FC03	**EN**: I can interact with these robots. **PT:** Creio que conseguiria interagir com estes robôs.	
	FC04	**EN**: I can communicate with these robots. **PT:** Creio que conseguiria comunicar com estes robôs.	
Hedonic Motivation	**HM01**	**EN**: I would enjoy interacting with these robots. **PT:** Gostaria de interagir com estes robôs.	Heerink et al. (2010)
	HM02	**EN**: I find these robots enjoyable. **PT:** Considero estes robôs divertidos.	
	HM03	**EN**: I find these robots fascinating. **PT:** Considero estes robôs fascinantes.	
	HM04 (R)	**EN:** I find these robots boring. **PT:** Considero estes robôs aborrecidos.	
Social Presence	**SP01**	**EN**: I can imagine these robots as living beings. **PT:** Consigo imaginar estes robôs como seres vivos.	Heerink et al. (2010)
	SP02	**EN**: Sometimes I think these robots are real people. **PT:** Por vezes, penso que estes robôs são pessoas reais.	
	SP03	**EN**: Sometimes these robots seem to have real feelings. **PT:** Estes robôs parecem ter, por vezes, verdadeiras emoções.	
Sociability	**SB01**	**EN**: I think these robots would be pleasant to interact with. **PT:** Penso que seria agradável interagir com estes robôs.	Heerink et al. (2010)
	SB02	**EN**: I feel that these robots would be able to understand me. **PT:** Sinto que estes robôs seriam capazes de me compreender.	
	SB03	**EN**: I consider that these robots would be pleasant conversational partners. **PT**: Considero que estes robôs irão proporcionar conversas agradáveis.	
	SB04	**EN:** I think these robots are nice. **PT:** Considero estes robôs simpáticos.	

UI02* and PE04*(R) were replaced by UI02 and PE04, due to the pre-test; EE04**Removed;
(R) Reverse Scaled;
EN:English; PT:Portuguese;

3.2. Data Gathering Procedure

To estimate the proposed conceptual model, data was gathered from potential users; for this purpose, a questionnaire was developed. Firstly, due to the complexity of the object of this study, social robots, a definition of these systems, with emphasis on the context of public places, was selected to give the respondents the required knowledge to answer the questionnaire. This definition was based on the one provided in Graaf et al. (2017), adapted to the context of the present study:

"Social robots are developed to function autonomously in ordinary environments, such as malls, museums and airports. These systems are able to understand basic social scenarios and react accordingly, by following stipulated human social norms. These systems are developed to work with humans and are able to communicate in a humanlike way, through supportive gestures and facial expressions, in addition to natural language. In public places, these systems are mostly assigned the tasks of:

- *Guide - in airports guiding passenger to their gate, in retail stores guiding clients to the items they want, and in museums guiding visitors throughout exhibitions;*
- *Information source – in airports to give information about gate, WC and other places, such as stores, luggage belts, etc., and in malls and in supermarkets, announcing and informing clients of promotions and the location of stores and items;*
- *Promotor - advising (promoting) the clients of products to buy and shops to visit, possibly giving discount vouchers to interested clients"*

In order to show how these robots perform in the context of this study, a video was developed using SonyVegas Pro, a software for video and audio editing, also to integrate the questionnaire. This video compiles a few interactions of people with four social robots in Airports, Museums and Exhibitions, Supermarkets, Retail stores and Malls and lasts exactly 2 minutes and 07 seconds - the duration of the video was reduced for the final questionnaire, in the first two pre-tests the video lasts approximately three minutes. This video was posted on a social media platform, YouTube, for the purpose of the questionnaire, and can be seen in https://www.youtube.com/watch?v=3kHKsaKlTbo. It was decided to do this video as an alternative to real-life experiment, due to the lack of resources to perform it. Also, the use this indirect method is frequently used and has been empirically validated in the field of HRI (Giger & Piçarra, 2018).

The robots selected for this study were considered the latest and most successfully employed nowadays, in the context of the present study. These robots are Spencer, Cruzr, Promobot and NAVii. The robots are displayed in Figure 21. in the same order as aforementioned - for more information consult Table 18 Appendix B.

Figure 21: Social Robots used in this research. From left to right: Spencer, Promobot, NAVii and Cruzr.

Spencer is the result of an EU-funded project involving six Universities and two industrial partners, being one of them KLM. The project started in April 2013 with 36 months of duration. This robot was developed to assist, inform and guide passengers in large and busy airports. Also, the robot has the particular task of guiding passengers of connecting flights conveniently and efficiently from their arrival gate to the passport control.

Cruzr is a Customized, Cloud-Based, Intelligent Humanoid Service Robot. This is, between the robots used in this study the only one that has a distributor in Portugal, Beltrão Coelho. This high-tech robot has been developed to be deployed in a variety of industries, domestic and public environments. CRUZR is able to recognize faces and objects, move with notion around unstructured environments and communicate naturally, what allows it to perform a wide range of tasks, from promotor, to welcoming host and even to museum guide or retail salesman.

Promobot is an autonomous robot presenting the latest technologies, that is able to recognize and remember a person, understand speech and communicate with natural language, move in unstructured environments, perform analytical reports and integrate any business platform. With such skills, this robot has been considered to be employed in airports, museums and exhibitions, retail and as an employee of any business.

NAVii is an autonomous retail service robot. Depending on the branding it changes its name to OSHbot, Lowebot or Bevbot and has already been installed in a few retail surfaces in the USA. This robot was developed to help customers with simple questions and to monitor inventory and analyse real-time data, thus, enabling more time for employees to focus on other tasks and helping in recognition of patterns or gaps, that are essential to consider in the retail business.

The questionnaire was built using Google Forms, as it is a free-of-charge, very useful and intuitive platform. As previously mentioned, the constructs of the model were measured with reliable scales, withdrawn from the reviewed literature on social robot acceptance models. Furthermore, every item was adapted to the context of public spaces and to the design of the present study. The items on these measurement scales were presented in 7-point Likert scale, from 1 being completely disagree, to 7 being completely agree with the statement respective to each item of every construct. Other questions in the questionnaire besides the ones related to constructs of the conceptual model did not follow this framework, instead they were simple multiple choice questions, and were included and developed to gather demographic data and find out if participants had any previous experiences with robots. Since this study was performed in

Portugal, the questionnaire was written in Portuguese, which required the translation of each item on every measurement scale chosen for the constructs.

A. First Pre-test

The first questionnaire was divided in two sections. The first section of the questionnaire addresses to demographic data such as age, gender, educational level and previous experience with robots. These items were measured with a simple multiple-choice question each. The second section is focused on testing the conceptual models of social robot anticipated acceptance in public spaces and to compare the four robots that integrate this experiment. For this, respondents were given the aforementioned definition of social robots, with emphasis on public spaces. Following this definition, and in order to give the respondents a visual notion of how these systems perform and what do they do in the context of public spaces, a brief video of four social robots in public spaces was incorporated in the questionnaire, with the duration of approximately 2 minutes and 50 seconds. As in the video, four robots with different functions and appearances were presented, it was intended, at first, to compare the results for each these robots. For this, all the items were rewritten in the singular form, (e.g. the statement “I find these robots easy to use.” was rewritten as “I find this robot easy to use.”), and for each statement, respondents had to answer once for each robot. Also, to ensure that the respondents knew which robot they were answering to, a figure of the four robots, was displayed before every 3 or 4 statements, as shown in the Figure 22, withdrawn from the questionnaire used in the first pre-test.

This questionnaire was sent to 23 individuals via email, WhatsApp and Facebook, with the objective to evaluate whether, or not, there were significantly different answers for each robot. The questionnaire lasted more than 15 minutes to fill. In addition to this, respondents were asked to give their opinion and suggest improvements on the form, statements and organization of the questionnaire.

Figure 22: Example of the first pre-test layout, from Google Forms

Unfortunately, results showed that on average, each respondent answered with the same value for all the robots in more than 72% of the statements. In other words, for nearly 22 out of the 30 statements presented, the answer was exactly the same for all the four robots. Therefore, as the variability of the answers between robots was that small, it was assumed that it was not possible to evaluate and compare these four robots, as respondents did not differentiate them

when answering the questionnaire. Thus, the singular form of statements was brought back to plural and it was decided not to distinguish these robots, instead to perform a broader questionnaire on these social robots in general. Nonetheless, to be able to do a comparison between the four robots, a new section was added to the next questionnaire.

The feedback from respondents tended towards forgetting what each robot did and where it was employed throughout the questionnaire. Some suggestions were presented, such as not referring to robot A,B,C,D, but mention their names, which is done in the second questionnaire. Another issue was raised from the respondents' feedback, *i.e.,* most respondents found the items UI01 and UI02* to be identical. To deal with this problem, the item UI02*, was replaced by UI02, which is an adaptation of the first item in the scale used to measure UI in Giger & Piçarra (2018).. Also, some respondents did not clearly understand the statement of the item PE04*. To address this issue, this item was replaced by an item derived from the original UTAUT2 model (Venkatesh et al., 2012), PE04.

B. Second Pre-test

This second questionnaire was divided in three sections. The first section is identical to the one used in the first questionnaire. The second section of this questionnaire is focused on testing the conceptual models of social robot anticipated acceptance in public spaces. The statements in this questionnaire were here built in the plural, as to evaluate social robots in public spaces in general, and not to evaluate particular robots, as was intended in the first questionnaire. The third section is relative to the respondents' preferences on each robot. For this section, an image of the four robots was displayed, now presented with the names of the robots instead of a letter (A,B,C,D). Then participants were presented with three statements (1 - I would like to interact with this robot in public spaces; 2 - This robot appears to have very good social skills; 3 – I like the appearance of this robot;), to be answered for each one of the robots in a 7 point Likert scale, and finally a "Share of Heart" multiple choice question is presented: "Identify the robot you would prefer to interact with in public spaces".

This questionnaire was sent to 18 individuals via email, WhatsApp and Facebook for pre-testing. The duration of the questionnaire was less than 10 minutes, which was significantly shorter than the previous one. Again, respondents were asked to give their opinion and suggest improvements on the form, statements and organization of the questionnaire. The feedback from this second pre-test was much positive, with only one issue brought up. The item EE04, *i.e.,* "I think I can use these robots when there is someone around to help me.", was considered very confusing by the respondents, and thus it was excluded. For the final questionnaire, only another change was made; this was relative to the issue mentioned in the first pre-test, forgetting the robots' performance and field of application. Thus, it was decided to include at the start of the third section the video presented at the beginning of the survey, to be consulted if respondents needed a reminder of the robots' capabilities and employment area.

C. Final Questionnaire

The final questionnaire was just an improved version of the one used in the second pre-test, with some minor adjustments. Besides the ones previously mentioned, a reduction of the video's size was performed, reducing it in 43 seconds, from 2 minutes 50 seconds to 2 minutes 07 seconds. Thus, the questionnaire is divided in three sections, a first section addressing demographic data, a second section addressing the constructs used in the conceptual model proposed in this study and a third section addressing the respondents preferences relative to the four robots presented.

A display of the questionnaire's format is displayed in Figure 29 Appendix C. The link to the questionnaire was sent by email, Facebook, and WhatsApp to family and friends - https://forms.gle/a53WS4u3atdfkoVf9. 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 less than 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

As observed previously, throughout the review of related work (Section 2.3.2.), to test conceptual models of social robot acceptance, most researchers wielded the SEM. As such, this strategy chosen for this study is composed by three parts (Figure 23). At first a preliminary analysis of the data is performed in order to scrutinize the sample and select only valid answers for the following analyses. The second 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, in fourth, 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.

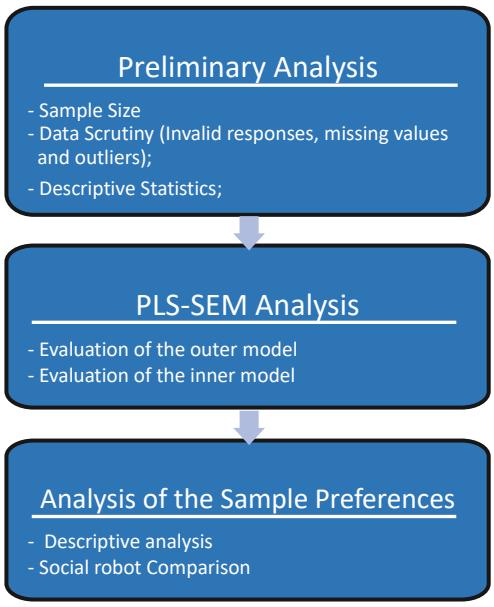

Figure 23: Data analysis Strategy

3.3.1. Preliminary Analysis

A. Sample Size and Data Scrutiny

Several guidelines are suggested to determine the minimum sample size have been presented such as the 10 times rule (Barclay et al., 1995), that suggests that the minimum acceptable sample size should either be ten times the largest number of formative indicators used to measure a single construct, or 10 times the largest number of structural paths directed at a particular construct in the model. Following this rule, it can be concluded that for the proposed model in this study, whose indicators are all reflective and the largest number of structural paths directed at one single construct is 7, the minimum sample size required is of 70 or more participants. Another guideline is given by (Cohen, 1992). The author presented a table that displays the minimum sample size to achieve minimum R^2 values of 0.10, 0.25, 0.50 and 0.75 for the endogenous variables for the significance levels 1%, 5% and 10%, for an assumed statistical power of 80% and the for the number of exogenous variables that explain the endogenous variable (Hair et al., 2017). For the proposed model of this study, the number of exogenous variables that explain the endogenous variable is 7, thus, the maximum, *i.e.,* for a significance level of 5% and to achieve minimum R^2 values of 0.10 in any construct, minimum sample size is of 166 observations. Notwithstanding the recommendations given by the guidelines to determine the minimum sample size required for the proposed model of this study of >70 and of >166, it was decided to gather at least 300 observations, to have a good margin for invalid responses and outliers, ensuring a good sample size.

Before assessing the results from the model, the sample needs to be analysed to determine invalid responses, missing values and extreme outliers. To analyse the existence of invalid responses due to straight lining, the answers to the questionnaire, more specifically only the answers to the section referent to the model's constructs, will be evaluated for their standard deviation relative to the mean of all these answers. Microsoft Excel was used for this procedure. If the Standard deviation of all the answers given to the statements relative to the constructs was lower than 0.5, the response relative to this value, would be thoroughly inspected. The inclusion of a reverse indicator in the questionnaire was very helpful to determine whether an answer was or not valid. If the participant answered with the same value for a normal and for a reversed indicator of the same construct, there is an evident lack effort from this participant and thus, his answer is excluded.

To evaluate the amount of missing values, the "Missing Value Analysis" option in IBM SPSS 23 was used to determine the number of missing values in every question on the survey. These results were then exported to Microsoft Excel for the minor calculations of the percentage of missing data in every variable. Kline (2011) suggests that if the percentage of missing data in one variable is less than 5%, there is no need to be concerned.

To check for the existence of multivariate outliers, the Mahalanovis distance was calculated in the SPSS 23, deriving as a variable. The threshold for the value for division of the Mahalanobis distance by the number of degrees of freedom, *i.e.,* the number of variables in the

model, was decided to be set at a conservative value of 3, in a way that a result higher than this, is considered a multivariate outlier.

B. Descriptive Statistics

In this step of the preliminary analysis, the descriptive statistics of the sample are displayed and analysed. The demographic results from the questionnaire are analysed with the frequency and the percentage, while the scores of the indicators of the model are analysed via frequency, maximum and minimum values, mean, variance and standard deviation. Finally, the skewness and kurtosis values for each indicator are inspected to verify if there is evidence of a non-normal distribution.

3.3.2. Analysis with PLS-SEM

According to Lowry & Gaskin (2014), statistical analysis techniques are divided in two generations, the first generation (1G) and the second generation(2G): *"1G techniques are statistical methods, such as correlations, regressions, or difference of means tests (e.g., ANOVA or -tests), that are well suited to simple modelling scenarios."*, and *"2G techniques (such as SEM) are statistical methods for modelling causal networks of effects simultaneously - rather than in a piecemeal manner. SEM offers extensive, scalable, and flexible causal-modelling capabilities beyond those offered by 1G techniques. 2G techniques do not invalidate the need for 1G techniques however."*

The SEM is a multivariate statistical technique that aggregates other statistical methods (namely, factor analysis and multiple regression analysis) to investigate a set of relationships between constructs in a conceptual model comprising independent (exogenous) and dependent (endogenous) variables. In other words, it allows the evaluation of a set of hypothesized relationships between unobserved constructs (latent variables) measured with sets of observed variables (measurement items/indicators). There are two main strategies of SEM, the covariance based (CB-SEM) and the variance based or partial least squares (PLS-SEM). The CB-SEM estimates the parameters of the model with the intention that the difference between the estimated and the sample covariance matrices is minimized. On the other hand, the PLS-SEM estimates the parameters of the model, maximizing the explained variance of the endogenous variables. The PLS-SEM is more appropriate for exploratory research, focusing more on prediction, while the CB-SEM is only used for confirmatory work, *i.e.,* for well-established models. While the CB-SEM requires large data samples, multivariate normality of the data and difficultly deals with complex models, the PLS-SEM is a non-parametric method, which makes no data distribution assumptions; additionally, this method works with small samples and very complex models. (Hair, Sarstedt, Ringle, & Mena, 2012; Lowry & Gaskin, 2014; Samani, 2016).

Therefore, as this study is of an exploratory nature, exploring the extension of the UTAUT2 model to the field of social robotics in public spaces, the PLS-SEM was considered the most appropriate for this research.

The application of the PLS-SEM follows the guidelines given by Hair et al. (2017). The software chosen was the SmartPLS 3.2.8, and some support to this software was given by IBM SPSS 23 and Microsoft Excel. The methodology applied is depicted in Figure 24.

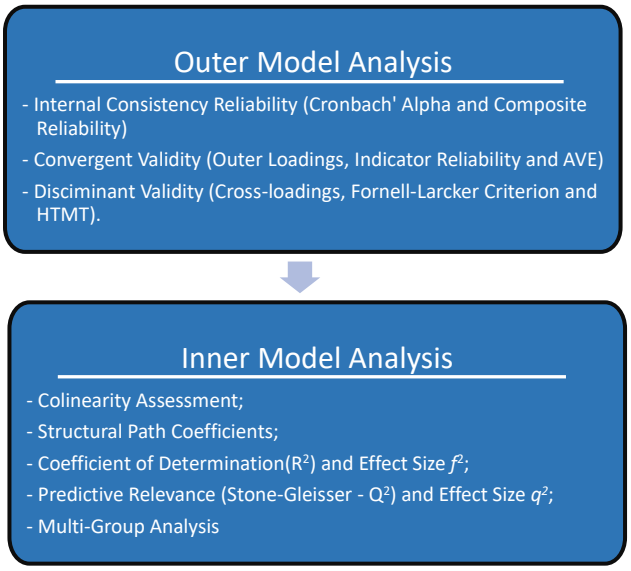

Figure 24: The PLS-SEM methodology, adapted from: Joseph F. Hair et al. (2019)

A. Outer Model Analysis

When using the SEM for model testing, the first phase of the result analysis is to evaluate the measurement models. For this, the reliability and the validity of the measures used for each construct is analysed. In a reflective model, such as the one proposed in this study, to assess the reliability, one should evaluate the Internal Consistency Reliability. To assess the validity of these measurement models, it is recommended to analyse Convergent Validity and Discriminant Validity (Hair et al., 2019; Hair et al., 2017). To compute the methods used to determine the aforementioned criterions, the SmartPLS 3.2.8 was used.

I. Reliability Analysis

Reliability addresses to the extent which a measure produces the same score each time it is run, with all other variables being equal. Internal consistency is a reliability measure that refers to the extent to which the indicators measures various aspects of the same characteristic or construct. The Internal Consistency Reliability has three methodologies to be determined, the Cronbach's Alpha, the Composite Reliability (CR) and the Rho A, which was not assessed in this study, as the Cronbach's Alpha is the most frequently used and the CR is considered the most reliable.

The Cronbach's alpha (α) gives an approximation of the reliability by assessing the intercorrelations of the indicators. Values of the Cronbach's alpha between 0.60 to 0.70 are reasonable in exploratory research, while in confirmatory research, values between 0.70 and 0.90 are recommended.

The Composite Reliability method takes under consideration the outer loadings of the different indicators. The thresholds for the values of CR are the same as for Cronbach's alpha, between 0.60 to 0.70 in exploratory research, and between 0.70 and 0.90 in confirmatory

research. Values of higher than 0.95 can be a problem, as they determine that indicators might be redundant. Since the Cronbach's alpha is considered to underestimate, while the CR tends to overestimate reliability, the inclusion of both measures is recommended as the true reliability would lie between the two methods (Hair et al., 2017, 2019).

II. Convergent Validity

Convergent validity is achieved when an indicator correlates positively with the other indicators in the same construct. As, in a reflective measure, the indicators are considered different ways of measuring the same construct, the indicators should "*converge or share a high proportion of variance".* The methods used to analyse this convergent validity, are the inspection of the outer loadings and of the Average Variance Extracted (AVE) (Hair et al., 2017).

The minimum required value of a loading is theoretically, that it must be statistically significant; nonetheless, the recommended value of the loadings is 0.70 or higher. The reason for this value is that the square of the outer loading is how much the variation on an indicator is explained by the construct, and thus, the value 0.70 is nearly equivalent to an explanation of this variation on 50%. Though, in exploratory studies it is strongly recommended to inspect loading between 0.40 and 0.70 and verify the changes its removal brings to the composite reliability and to the AVE. Indicators with loading values below 0.4 must be excluded.

The method to address the issue of convergent validity is the AVE, which is defined as the mean value of explained variance of the indicators by the construct. Basically, it is the sum of the squared loadings of all the indicators in a construct, divided by the number of indicators; it is recommended that the AVE is higher than 0.50, thus ensuring that the construct explains at least 50% of the variation of the indicators (Hair et al., 2017, 2019).

III. Discriminant Validity

Discriminant validity refers to the empirical distinction of constructs, *i.e.,* for a model to have discriminant validity, the constructs that this comprises must be unique so that two constructs are not measuring the same concept. To evaluate discriminant validity, there are three methods to be used, *i.e.,* Cross-loadings, the Fornell-Larcker criterion and the Heterotrait-Monotrait ratio (HTMT) of correlation. While the first two are considered are not considered the most reliable, as they perform poorly in some cases, the third is considered the most appropriate to be applied (Henseler et al., 2015).

Cross-loadings consist on the correlations of the indicators' loadings with each of the constructs. This measure is given by SmartPLS 3.2.8 on a table that has the constructs each column and the indicators on each row. According to this method, discriminant validity is true if the correlation between the indicators of a construct and the construct they measure are higher than then all the correlations between these same indicators and all the other constructs (highest on the row), and higher than all the correlations between the construct they are measuring and all the other indicators measuring other constructs (highest on the column).

The Fonell- Larcker criterion is very simple, basically it argues that, to confirm discriminant validity, it is required that the values of square root of the AVE of each construct are higher than

the correlations between this construct and all the other. In other words it follows the same logic as the previous method as, when these values are in a table of correlations between constructs, though instead of the correlation between a construct and itself, the square root of the AVE is in the diagonal of this table, the AVE has to be the highest value on the row and column it is in.

The HTMT was recently presented by Henseler et al., (2015) as an alternative for the other two methodologies, which had shown reliability issues in their research. The HTMT ratio of correlations, according to Hair et al. (2017), *"is the mean of all correlations of indicators across constructs measuring different constructs (i.e., the heterotrait-hetero method correlations) relative to the (geometric) mean of the average correlations of indicators measuring the same construct (i.e., the monotrait-hetero method correlations)".* - see Henseler et al. (2015) for a more detailed characterization. For this methodology, discriminant validity is achieved if the HTMT values are below the threshold value of 0.90 for conceptually related constructs and 0.85 for conceptually distinct constructs. Also, it is recommended to analyse the HTMT results from the Bootstrapping to check if the 97.5% upper bound of the confidence interval is below one, this way indicating discriminant validity (Hair et al., 2017, 2019).

B. Inner Model Analysis

After evaluating the measurement model's reliability and validity, the second phase of the result analysis is to evaluate the inner model, *i.e.* the structural path. The first step is to evaluate the collinearity issues of the model, using Tolerance and Variance Inflation Faction (VIF) values. The second step is to assess the structural path coefficients, by analysing the relevance (path coefficient values) and significance (t-statistics and p-values) of these structural paths. The third step is to Coefficient of Determination (R^2 and $R_{adjusted}^2$) and Effect Size (f^2), while the fourth and final step is the evaluation of the Predictive Relevance (Stone-Gleisser - Q^2) and Effect Size q^2. Also, Multi-group analysis was conducted to evaluate the influences of the demographic characteristics gender, age and experience, following the methodology of Matthews (2017). To compute these methodologies by determine the aforementioned criterions, the SmartPLS 3.2.8 was used.

I. Collinearity Assessment

The first step in the inner model analysis is the assessment of collinearity. Collinearity is the extent to which two exogenous variables (independent constructs) have a high correlation between them. Thus, they are not able to independently predict the value of the endogenous variable (dependent construct), *i.e.* they explain some of the same variance in the endogenous variable, reducing their significance.

The first way to analyse collinearity is to calculate the Tolerance. Tolerance is the amount of variance of one exogenous construct that is not explained by the other exogenous constructs on the model. The threshold for Tolerance has been established at 0.333 (conservative) or 0.20 (standard), meaning that a value lower than this might express a collinearity issue.

The other measure of collinearity, and the one used in this study, is the VIF, which is defined as *"degree to which the standard error has been increased due to the presence of*

collinearity" (Hair et al., 2017). The VIF equals to one divided by the tolerance and therefore, one can only assess one of these criteria, for which the VIF was selected. The threshold of the VIF is 3 (conservative) or 5 (standard), meaning that values of VIF equal to 3 or 5 or higher may indicate collinearity problems. In this study the threshold of 3 was selected. In these cases, it is recommended to review the model and consider excluding, merging or generating higher-order constructs to treat collinearity issues (Hair et al., 2017, 2019).

II. Structural Model Path analysis

The path coefficients (β) characterize the hypothesis of the proposed model, *i.e.,* the relations between the constructs, mentioned on Section 3.1.2. The path coefficients should be interpreted as standardized regression coefficients in a way that if there is a change in an exogenous variable by one standard deviation, the endogenous variable changes by β standard deviations. These values are usually range from -1 to +1 and the higher its absolute value, the stronger the relation, closer to -1 represents negative relation and closer to +1 indicates a positive relationship. Path coefficients values over 0.10 are generally considered to be a relevant relation (Hair et al., 2017).

To evaluate the significance of these path coefficients, which depend on their standard errors, the PLS-SEM resorts to bootstrapping for the calculation the empirical t-values and p-values. The Bias-Corrected and Accelerated (BCa) bootstrapping type is recommended by Hair et al. (2017). A path coefficient is considered significant when the t-value relative to that path coefficient is higher than the critical value, hence, the respective p-value is lower than the significance level selected. Significance levels of 10% are more often related to exploratory research, of 5% are usually used in marketing research and of 1% is sometimes also used in marketing research, more if the study is experimental. In the present research the 5% significance level was selected.

III. Coefficient of Determination and Effect Size

The coefficient of determination represents the in-sample predictive power or predictive accuracy of the model, *i.e.,* it expresses the total of variance of the endogenous variable explained by the exogenous variables. The R^2 equals *"the squared correlation between a specific endogenous construct's actual and predicted values"* (Hair et al., 2017). The values of R^2 range from 0 to 1, and even though its interpretation is dependent on the model's complexity and the research field, typically, R^2 values of 0.25 are considered weak, of 0.50 are considered moderate and of 0.75 are considered substantial (Hair et al., 2019; Hair et al., 2017).

To deal with biased results of the R^2, in models with higher complexity, and to compare models with different exogenous variables, the R^2 adjusted is recommended to be the one used. The R^2 adjusted takes into consideration the sample size and the number of exogenous variables in the model.

Additionally, one must also investigate how much the inclusion/exclusion of an exogenous affects the model's R^2; which is measured by the Effect Size (f^2). The thresholds for

the f^2 values are of 0.02, 0.15, and 0.35, respectively, for a small, medium, and large effect (Cohen, 1988) of the exogenous variable on the endogenous variable. If the values of f^2 are below 0.02, then, there is considered to be no effect of the exogenous variable on the endogenous variable (Hair et al., 2017, 2019).

IV. Predictive Relevance and Effect Size

Besides evaluating the Coefficient of Determination and its respective Size Effect, it is recommended to also assess the predictive relevance of the model, *i.e.,* the Stone-Geisser's Q^2. While the R^2, is a measure that indicates the in-sample predictive power or predictive accuracy, the Stone-Geisser's Q^2 is a criterion that reflects the out-of-sample predictive power or predictive relevance. If predictive relevance is present in a model, then it can be said that it *"accurately predicts data not used in the model estimation."* This method resorts to the Blindfolding technique to get cross-validated redundancy measures for each dependent latent variable.

Blindfolding is procedure takes into account a distance, D, to omit every d^{th} data point of the sample, as missing values, and then re-evaluates the model, with this missing data treated, for instance with the mean replacement method. This procedure is performed iteratively, starting on the following data point, then in the previous iteration, until every data point has been omitted. The omission distance D must be a value between 5-10 that, when dividing the sample by this distance, D, the result cannot be an integer. The threshold for predictive relevance is set for values above 0.

As the Coefficient of Determination (R^2), one can also assess the relative predictive relevance of the exogenous constructs, *i.e.*, the effect size (q^2). As the effect size f^2, the thresholds for the effect size q^2 for small, medium and large predictive relevance for the endogenous construct are, respectively, 0.02, 0.15 and 0.35.

V. Multi-Group Analysis

The final step in the PLS-SEM analysis is the Multi-group analysis (MGA), a process to evaluate whether different groups of participants show differences in the model parameters between these groups. The present research attempts to verify whether there are differences in the path coefficients of the proposed model, within the UTAUT2 groups age, gender and robot related experience. To assess whether there are statistically significant differences between each path coefficients within each group, the permutation methodology suggested by Matthews (2017) was used. Following Matthews (2017), at first one must identify the different groups to be compared. Secondly, for each of the comparisons, the model constructs must be evaluated for invariance, using the Measurement invariance of composite models (MICOM) procedure. Finally, the results from the permutation are assessed and interpreted. In addition, to find out if the differences between path coefficients of the compared groups are statistically significant, the results from the Parametric and Welch-Satterthwait Tests were inspected, alongside the results from the PLS-MGA method. The permutation and the results from these three tests were computed in SmartPLS 3.2.8; 1000 permutation samples were selected with a two-tailed test for the 0.05 significance level.

3.3.3. Robot comparison: a brief analysis of the sample's preferences

A brief analysis of the results from the third part of the questionnaire is performed, by evaluating the mean values resultant from the answers given for each robot in the three selected characteristics (likability, sociability and attractiveness). In addition, the "Share of heart" question is addressed. Thus, enabling the comparison of the appearance between the four robots, Oshbot (Mechanoid), Spencer (Mechanoid with head), Cruzr (Anthropomorphic robot) and Promobot (Humanoid).

4. Results

This chapter reports the practical application of the methodology, defined in Chapter 3. All the processes of the methodology and the specific steps take on in each of the phases are herein detailed. For the analysis of the data the softwares SmartPLS 3.2.8, IBM SPSS 23 and Microsoft Excel were used.

4.1. Preliminary analysis

4.1.1. Sample Size and Data scrutiny

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). To check for straight lining, *i.e.*, giving the same answer to all questions, the standard deviation of each response was calculated in excel, and the lowest values were inspected. To ensure a participant filled the questionnaire with a straight line, the only reverse indicator was analysed, and if the answer was the same as the non-reverse items, then it was clear that the participant did not even take the effort to read the survey carefully, and just filled all the scales with the same value. These full straight lining or nearly full accounted for five answers, which were excluded. Additionally, the lack of effort was also evaluated partially, participants with more than ten consecutive equal responses were also excluded from the sample, thus the sample was reduced to 258 valid answers.

To detect multivariate outliers, the Mahalanobis was used. This procedure was performed in SPSS. 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.

Afterwards, the sample was analysed for missing data. In the first section of the questionnaire, demographic data, there was one missing answer to the robot experience question. In the second section of the questionnaire, the indicators of the model's constructs, there were, surprisingly, only found six missing values, which is way under the 5% threshold, given by Kline (2011), therefore, mean replacement is recommended to be used as the substitution method of the missing values (Hair et al., 2017).

4.1.2. Descriptive Statistics

As displayed in Table 2, the sample is composed by 53,7% male and 46,3% female individuals, which is a sufficiently homogenous sample. This cannot be said for the age groups, as most respondents, *i.e.,* 67.8%, are in between 18 and 34 years old (see Table 2). The second larger age group in this sample is between 35 and 54 years, only representing 17.3%, followed by respondents between 55 and 64 years with just 10.6%. Furthermore, there are five respondents with less than 18 years (2%) and six with more than 64 years (2.4%).

When it comes to the occupation of the participants, as depicted in Table 2, almost half of the participants work on the behalf of other (47,1%), followed by a substantial sample of students of 31.4%, followed by a reasonable amount of self-employed respondents of 15.3%. The other four options, only accounted for 6.4%, with 0.4% unpaid family workers, 1.6% of unemployed participants, 2.4% of Employers and also 2% of other type of occupation.

Looking to the education and occupations of the participants, there are two main groups, *i.e.,* 39.6% of participants have a Bachelor's degree while 37.6% have a Master's degree. As observed, 10.6% of the sample had finished their education in High School and only 1.2% of the sample only finished in basic school. Post-secondary Education participants in this sample represent 5.9%, while 4.7% had a PhD. Other kind of education not included, only comprised 0.4% of the participants. Such results, thus, reveal a quite instructed sample.

Finally, robot related experiences, it was verified a quite homogenous sample between respondents that had some experiences with robots (45.5%), and the ones who never had an experience with robots (50.6%), leaving the sample of respondents who had many experiences with robots with only 3.5% of the total sample, also, as previously mentioned there was one missing answer (0.4%).

Table 2: Socio-Demographic Data

Gender		**Education**	
Male	137 (53.7%)	Basic Education	3 (1.2%)
Female	118 (46.3%)	High School	27 (10.6%)
		Post-Secondary Education	15 (5.9%)
Age		Bachelor's Degree	101 (39.6%)
Minus than 18 years	5 (2%)	Master's Degree	96 (37.6%)
18-34 years	173 (67.8%)	PhD	12 (4.7%)
35-54 years	44 (17.3%)	Other	1 (0.4%)
55-64 years	27 (10.6%)		
More than 64 years	6 (2.4%)	**Robot Related Experience**	
		No	129 (50.6%)
Occupation		Yes, a few times	116 (45.5%)
Student	80 (31.4%)	Yes, many times	9 (3.5%)
Unemployed	4 (1.6%)	Not Reported	1 (0.4%)
Work on the behalf of other	120 (47.1%)		
Self Employed	39 (15.3%)		
Unpaid Family Worker	1 (0.4%)		
Employer	6 (2.4%)		
Other	5 (2%)		

Having assessed the general demographic data of the questionnaire, Table 3 provides the descriptive statistics of the second section of the questionnaire, the results from statements referent to the constructs of the proposed conceptual model.

Observing the descriptive statistics, one can realize that, in average, the sample expresses a quite high intention to use social robots in public spaces, with all values of the indicators of UI above 4.75, way above the median value of the seven-point Likert scale of 3.5. Alongside UI, the indicators of PE reflect high values, all above 4.60, indicating that, in average, for this sample, the robots presented in the video were considered quite useful. For the construct EE, participants considered social robots in public spaces to be easy to use, with mean values above 5.10 for the three statements referent to this construct. Additionally, SN expressed totally different mean values for the items referent to “Social Influence” (SN01 and SN02) than for the ones referent to “Image” (SN03 and SN04), expressing a high expectancy (mean values above 5.00) that other people will find these Social robots for public spaces interesting and attractive. Notwithstanding, in average, the sample expressed that the usage of such robots in the context of public spaces will not increase that user’s social image/prestige, with both items representing a mean value of 2.85, way under the median value of 3.5 for seven-point Likert scales. Observing the values of the items for FC, one can conclude that participants, in average, consider themselves to have the necessary skills to use such robotic systems (all mean values above 5.55). Also, participants expressed high values for the items of HM (all above 4.60), suggesting that the use of such robotic systems is considered fun for this sample. On the other hand, the robots were not perceived as living beings, with all the mean values of the items referent to SP below 2.30. Finally, despite finding these social robots pleasant, *i.e.,* the mean value of SB01 is 4.41, they were not considered to have good social skills, with two items (SB02 and SB03) below the median value for the employed seven-point Likert scale and the other one (SB04) very close to that value (3.56).

As observed in Table 3, the entire scale was used for all the items, with answers ranging from 1 (totally disagree) to 7 (totally agree).

Values of skewness and kurtosis were also inspected indicating that, for the recommended thresholds of $-1 < sk < 1$ for univariate skewness and of $-1.5 < ks < 1.5$ for kurtosis (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, as expected, a non-normal distribution.

Table 3: Descriptive statistics of the answers to the questionnaire

	N	Mean	Std. Dev	Min-Max	Skewness	Kurtosis
UI01	255	5,01	1,411	1-7	-,420	-,416
UI02	255	4,95	1,526	1-7	-,571	-,231
UI03	253	4,77	1,420	1-7	-,358	-,299
PE01	255	4,72	1,586	1-7	-,626	-,221
PE02	255	4,66	1,608	1-7	-,526	-,465
PE03	255	4,72	1,388	1-7	-,568	-,032
PE04	255	5,00	1,457	1-7	-,825	,403
EE01	255	5,48	1,301	1-7	-,897	,592
EE02	255	5,32	1,313	1-7	-,833	,609
EE03	255	5,19	1,468	1-7	-,705	,017
SN01	254	5,22	1,225	1-7	-,481	-,023
SN02	255	5,00	1,340	1-7	-,554	,176
SN03	255	2,85	1,680	1-7	,434	-,946
SN04	255	2,85	1,721	1-7	,466	-,982
FC01	255	5,65	1,268	1-7	-,994	,763
FC02	255	5,81	1,212	1-7	-1,159	1,420
FC03	255	5,67	1,302	1-7	-1,120	1,135
FC04	255	5,57	1,335	1-7	-,993	,620
HM01	255	5,11	1,615	1-7	-,761	-,144
HM02	255	4,69	1,656	1-7	-,435	-,604
HM03	255	4,87	1,717	1-7	-,630	-,493
HM04	255	5,32	1,542	1-7	-,759	-,156
SP01	255	2,07	1,408	1-7	1,193	,533
SP02	255	2,05	1,387	1-7	1,462	1,563
SP03	255	2,25	1,493	1-7	1,108	,311
SB01	254	4,41	1,526	1-7	-,358	-,483
SB02	254	3,34	1,741	1-7	,210	-1,048
SB03	254	2,40	1,497	1-7	,923	,082
SB04	255	3,56	1,659	1-7	-,007	-,845

4.2. Analysis with PLS-SEM

This chapter presents the results of the study following the methodology proposed by Hair et al. (2017), that is specified in the previous chapter. This methodology is divided in two steps: the first step is to evaluate the outer model, to verify if the measures are adequate for the constructs that they are measuring, *i.e.,* its reliability, convergent validity and discriminant validity. The second step is to analyse the inner model, *i.e.,* to check for collinearity issues in the model, then interpret the results from the R^2 (explained variance) and the path coefficients in order to empirically support or not the hypotheses proposed for this conceptual model. Figure 25 displays the original model and its respective results from the SmartPLS 3.2.8. The results were calculated with the Consistent PLS-SEM Algorithm (PLSc) with the following settings: for the initial calculations all the latent variables were connected, the weighting scheme used was the Path Scheme for all calculations, with the expectance of the Collinearity Statistics, for which the Factor weighting scheme was chosen. The maximum number of iterations was set at 1000, while the stop criterion was set at 10^{-7}. To handle the missing data, the mean replacement method was selected. For the Bootstrapping, the Consistent Bootstrapping was chosen accordingly to the PLSc, the settings

were: 500 subsamples, with parallel processing, while the Confidence Interval Method chosen was Bias-Corrected and Accelerated (BCa) and the two-tailed test type selected, with a significance level of 5% (0.05).

Finally, for the Blindfolding, that only require the omission distance, for which the value 9 was selected, as the number of data points of 255 divided by 9 equals 28.(3), which is not and integer and it is a value between 5 and 10.

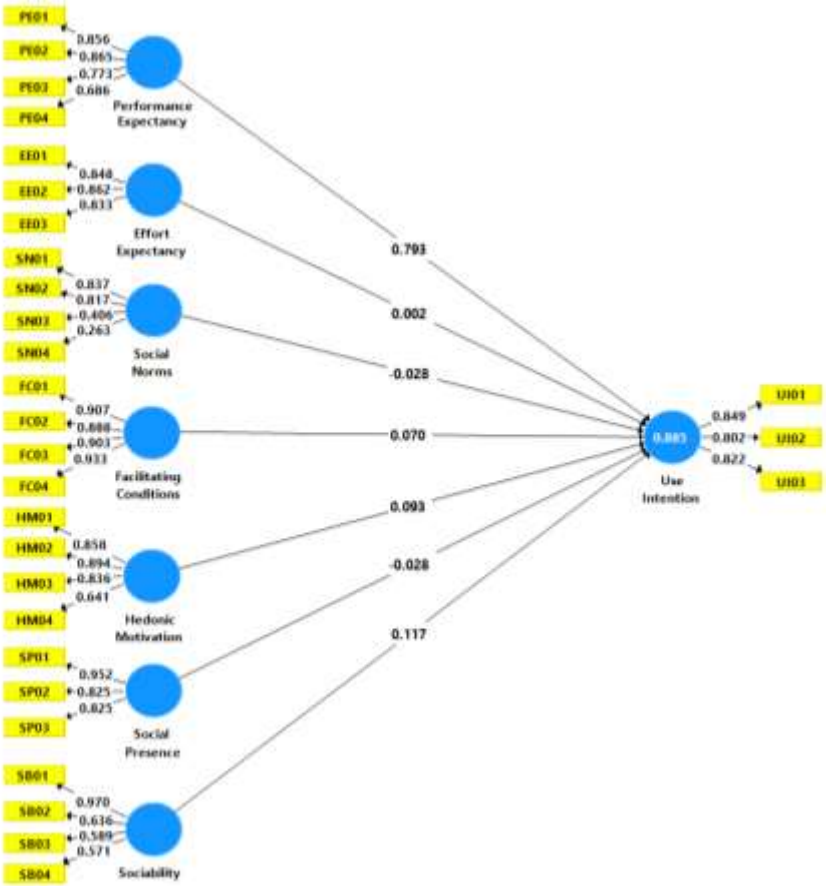

Figure 25: PLSc Results for the Original Model

4.2.1. Outer Model Analysis

A. Internal Consistency Reliability

To evaluate the internal consistency reliability both the Cronbach's Alpha and the Composite Reliability 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, indicating Internal Reliability - values for the original model are presented in Table 19 of Appendix D. On the other hand, when analysing the CR it can be verified that for the construct SN, internal consistency reliability was not achieved (0.692), as observed in Table 19 of Appendix D. Nonetheless, the value (0.692) and its close the threshold value of 0.70 according to Hair et al. (2017), so there is still need to address the convergent validity, approached in the following analysis, before making any changes.

Consequence of the alterations performed in the next section, due to convergent validity issues, the internal consistency reliability was achieved completely, as the composite reliability of the construct SN improved from 0.692 to 0.833, as observed in Table 20 of Appendix D. Internal

consistency was preserved until the final model, presenting high values for both the Cronbach's Alpha and the Composite Reliability of all constructs above 0.830, which is way above the thresholds set the two criteria of 0.70 - see Table 4. Thus, such results demonstrate the achievement of internal consistency reliability for the entire model. All calculations were performed by the SmartPLS 3.2.8 software, alongside the estimation of the model with the Consistent PLS algorithm.

B. Convergent Validity

To evaluate the convergent validity of the model, the first step is to observe if the outer loadings of the indicators are above the threshold of 0.70, while 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, one can observe that in the original model (Figure 25), the outer loadings indicators for 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. These results disprove that SN is composed by "Social Influence" (SN01 and SN02) and "Image" (SN03 and SN04) in a reflective measurement (proposed in Section 3.1.3.), illustrating that these variables, are too conceptually different and thus, SN was only measured with indicators from "Social Influence". Although results are not reported due to document space restrictions, a model including "image/status" as a separate dimension was tested, and results showed a non-significant β-value of -0.040, basically maintaining the results obtained when this dimension was not included in the model.

Problems were also found on the construct SB as two of the indicators (SB03 and SB04) presented values below 0.60 (Figure 25). To deal with this issue, the first indicator SB01, although it represents the highest outer loading, it was considered the "outlier" of the four selected indicators. While the results for the other three indicators, indicate that there is convergence among them, the first indicator (SB01) was not relatable to the other three. Also, SB01 was considered the indicator that less expressed the concept of the construct, and therefore it was dropped. Such changes in the model, reflected no more problems with any of the indicators outer loadings, with all values above 0.60, not only right after these alterations, as it can be observed in bold in the diagonal of Table 21 of the Appendix D, but also for the final model, which is displayed in Figure 27 and in bold in Table 22 of Appendix D.

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, and has its threshold set at 0.50, which reflects that in average, at least every indicator explain 50% of the variance of the construct. As the AVE is dependent from the outer loadings of the indicators, thus,

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, as I can be seen in Table 19 of Appendix D. The alterations performed in the previous step, due to low values of the outer loadings (exclusion of SN03, SN04 and SB01), improved the values of the AVE in both of the problematic constructs. The AVE for SN increased from 0.40 to 0.715 and for SB from 0.505 to 0.514 as it can be seen in Table 20 of Appendix D. All the other constructs, presenting good values of the outer loadings, also, expressed good values of AVE, with all values above 0.60, *i.e.*, way above the threshold of 0.50. Thus, the original outer model suffered changes in order to achieve convergent validity. As observed in Table 4, the final outer model presents values of the AVE above 0.63, indicating convergent validity.

Table 4: 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**

C. Discriminant Validity

Having thus achieved internal consistency reliability and convergent validity of the outer model, the third and final step is to evaluate its discriminant validity. Therefore, in this step, all the changes performed previously are already taken under consideration. 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).

The first step is to inspect the cross-loadings of the indicators, which is presented in Table 21 of Appendix D. According to this criterion, the values of the indicator's outer loadings (presented in the diagonal, in Bold) must be higher than the values of the cross-loadings in the same row and line. As it can be observed in this table, discriminant validity was achieved for all the constructs, PE and UI, presenting some values of the cross-loadings between these constructs higher than the outer

loadings in the same row or line. Similar results were observed in the cross-loadings of the final model, as it can be seen in Table 22 of Appendix D.

The second step is the assessment of the Fornell-Larcker criterion. According to this 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 (represented in the diagonal of Table 19 in blue) for that particular construct. As observed in Table 23 of Appendix D, the value of the correlation between SB and SP (0.748), is higher than the square root of the AVE of SB (0.717), indicating possible problems in the discriminant validity of these two constructs, though it is not higher than the square root of the AVE of 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), suggesting there might be a lack of the discriminant validity between those constructs. When

evaluating the Fornell-Larcker criterion for the final model, one can observe that, according to this criterion, discriminant validity was not achieved between UI and PE, as the values did not change from the previous assessment (correlation=0.928, AVE_{UI}= 0.825 and AVE_{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 - Table 24 of Appendix D. Notwithstanding, discriminant validity was achieved between these constructs according to another criterion, that considers discriminant validity if the value one is not included in the confidence intervals generated by the bootstrapping. The highest value of 0.973 for the HTMT between PE and UI, in the percentile 97.5% (Table 25 of Appendix D). When assessing the final model, as observed in Table 6, despite achieving discriminant validity for the exogenous variables, the endogenous variable presented a value higher than the threshold, thus, in order to consider this construct discriminately valid, the confidence intervals were assessed, via bootstrapping (Table 26 of Appendix D). Again, results showed that the Value of one was not present (Hair et al., 2017). This is the last step in the assessment of the outer model, and thus, the next section focuses on the evaluation of the inner model. 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.

Table 5: 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 6: 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	

4.2.2. Inner Model Analysis

Having thus achieved internal consistency reliability, convergent validity and discriminant of the measurement models used for measuring the constructs of the proposed conceptual model, the inner model, *i.e.,* the proposed hypotheses (paths) and their influence on the endogenous variable (explanatory power - R^2), can now be assessed.

A. Collinearity Assessment

The first step in the analysis of the inner model is to inspect the model for collinearity, which can be problematic to the model estimation. The recommended threshold for PLS-SEM is 3 instead of 5, which is usually used in CB-SEM. Table 7 and Table 8 show the VIF values for each exogenous constructs, respectively for the model after the first changes and for the final model. For the original model, the results indicate a multicollinearity issue with the construct in the construct SB, with values above 3, as observed in Table 7. To deal with this multicollinearity issue, the model was thoroughly examined, starting by analysing the correlations between the constructs (Table 23 of Appendix D) and the cross-loadings (Table 21 of Appendix D), followed by the evaluation of a substantial amount of manipulations in the model (excluding and merging constructs). As a result, the construct SB was 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 by the fact that SB has been shown a determinant of both the other constructs (Heerink et al., 2010).

Therefore, it is interesting to note that, the model was run with SB as an antecedent of both HM and SP (Figure 26), and such influences were found relevant and significant - SB->HM (β=0.628; p-value=0.000); SB->SP (β=0.748; p-value=0.000) - and explaining around 39.4% of HM (R^2=0.394) and 56% of SP (R^2=0.560). Also, there was a significant total indirect effect of SB in UI (β=0.111; p-value=0.038). Notwithstanding, the inclusion of SB as antecedent of SP and HM, does not change any of the path coefficients in the final model, nor the value of the R^2 relative to UI. Therefore, it was decided to proceed without the dimension SB, this way evaluating a more parsimonious model.

Consequently, this alteration led to the structure of the final model (Figure 27), for which the values of the VIF for every exogenous construct are below 3, as observed in Table 8, and thus, reflecting no collinearity issues in the model.

Table 7: Collinearity Statistics - VIF

	VIF
EE	2.448
FC	2.398
HM	2.877
PE	2.163
SB	3.351
SN	1.896
SP	2.377

Table 8: Collinearity Statistics of the Final model - VIF

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

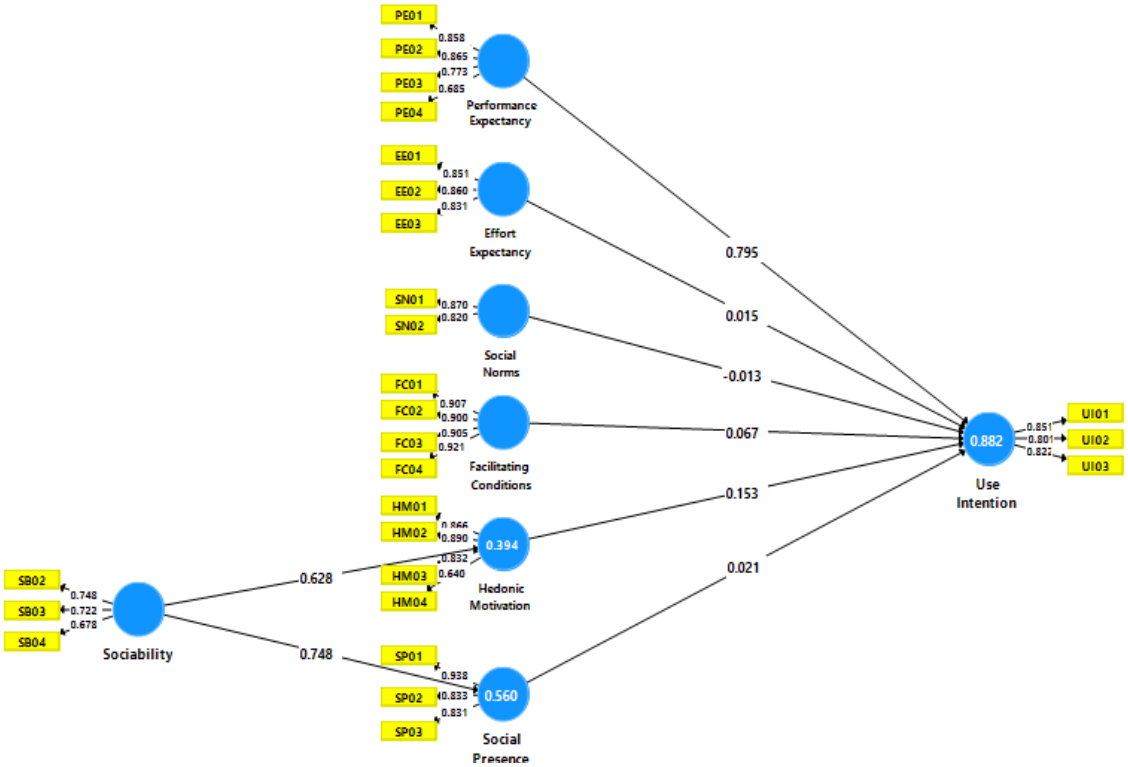

Figure 26: PLSc Results for an intermediate model with SB as an Antecedent of SP and HM

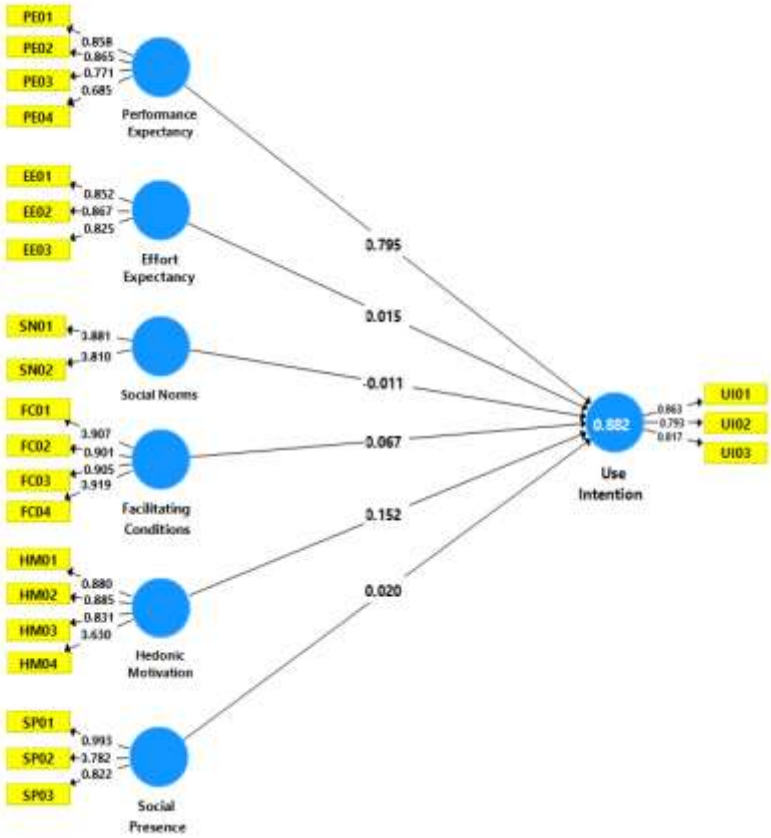

Figure 27: PLSc Results for the Final Model

B. Structural Model Path Analysis

The results from the path coefficients reflect only two constructs with some relevance, i.e. PE and HM, as depicted in Table 9. 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, as hypothesis 7 (H7) had already been excluded for collinearity issues, were not supported by the model evaluation, as not only their path coefficients were not relevant, they were also not significant.

Given the very high influence of PE on UI, it possible that, due to this result, the influences of the other non-significant dimension are affected. Therefore, a model without this dimension was run, and results compared to the final model - Figure 27. 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 9: 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

C. Coefficient of Determination and Effect Size

The results from the PLS-SEM algorithm express that the six exogenous variable of the model - EE, FC, HM, PE, SN and SP - explain about 88.2% (R^2=0.882, *p*-value=0.000; $R^2_{adj.}$=0.879, *p*-value=0.000) of the variance of the endogenous variable, UI. This value is essentially explained by only one variable, *i.e.* PE. The other significant construct is HM, though, with a lower impact on the variance of UI, as it will be observed afterwards. According to Hair et al. (2017), R^2 values of 0.19, 0.33 or 0.67 characterize a model as weak, moderate or substantial, respectively. Following this criterion, the proposed conceptual model for social robot acceptance by potential users in public spaces, has a substantial explanatory power (R^2=0.882) in explaining the endogenous construct UI of Social Robots in the context of Public Spaces.

After the interpretation of the Coefficient of Determination (R^2), the effect size of the exogenous constructs on the endogenous construct was assessed, revealing no effects from EE, FC, SB and SN, as expected, as their path coefficients were also very low, and were neither

relevant nor significant. 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. These results are shown in Table 10.

Table 10: Effect Size - f^2

	f^2
EE->UI	**0.001**
FC>UI	**0.016**
HM->UI	**0.083**
PE->UI	**2.481**
SN->UI	**0.001**
SP->UI	**0.003**

D. Predictive Relevance and Effect Size

In addition to the interpretation of the Coefficient of Determination (R^2) and the respective effect sizes (f^2) of the exogenous constructs on the endogenous construct, 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 relevance, and vice-versa, *i.e.* a value of Q^2 below zero indicates no predictive relevance. Findings revealed that UI has a Q^2 value of 0.532, indicating a strong predictive relevance according to the recommended threshold.

As assessed in the previous section, the effect size (q^2) in the predictive relevance is also computed, though, its calculation had to be performed manually on Microsoft Excel, with input values from the SmartPLS 3.2.8. The thresholds are the same as for the effect size (f^2), therefore, as it can be observed in Table 11, 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.

Table 11: Effect Size - q^2

	q^2
EE->UI	**0,01**
FC>UI	**0,01**
HM->UI	**0,04**
PE->UI	**0,34**
SN->UI	**0,01**
SP->UI	**0,01**

E. Multigroup Analysis

In this study, to perform MGA, the permutation method given by Matthews (2017) was followed and completed by also assessing the Parametric and Welch-Satterthwait Tests, as well as the results from the PLS-MGA method.

As the proposed model in this study has its roots in the UTAUT2, it was decided to evaluate the effects of the moderating variables for the UTAUT2, *i.e.*, gender, age and experience, in the relationships of this model, *i.e.,* the suggested hypotheses. Thus, each of these variables was divided in two groups to be compared. For gender, the sample accounted for 137 males and 118 females, for age, one group included 173 participants from 18-34 years and the other included 77 participants with more than 34 years and for experience, one group included 129 participants that did not have any robot experiences, while the other included 125 participants who had few

or many robot experiences. All groups fulfilled the minimum sample requirements for the following guidelines: the rule of 10 times the maximum number of paths or indicators for a single construct (Barclay, et al., 1995), which is 60 and for the rule for the minimum sample size given by Cohen (1992), suggests that a minimum sample size for 6 exogenous variables for the 5% significance level is 75 for a minimum R^2 of 0.25. Therefore, one must take special attention to the age group >34, that has a sample size (77) close to the minimum of 60 and 75 for each rule. This identification of groups is the first step of the MGA.

The second step is to test the model for invariance, resorting to the MICOM. Firstly, one must guarantee that there is configural invariance. This was guaranteed since the measurement model (indicators) and the data scrutiny are the same for the groups in comparison. Which was already achieved throughout the present study. Then, the compositional invariance is assessed. To achieve compositional invariance, the values for the Original Correlation must higher than or equal to the 5% quantile. If the value for the 5% quantile is higher than original correlation, invariance is not achieved for that construct, and it needs to be removed before proceeding. Results show that compositional invariance was achieved for all cases, with the exception of the construct SN when analysing robot experience, that failed to achieve invariance- see Table 27. Nonetheless, as the values are very close and this study is of an explorative nature, the construct was kept, maintaining the model structure for the three categorical variables. The last step of the MICOM is the composite equality. To achieve this, two criteria must be evaluated. The values for the mean and for the variance of the difference between the path coefficients, must fall between the values for their respective 2.5% and 97.5% confidence intervals. Results indicate that full invariance (both criteria fulfilled) was achieved in the age analysis. While in the robot experience analysis, FC and EE presented only partial invariance (one criterion fulfilled), in the gender analysis, also FC presented partial invariance and for SN, invariance was not achieved - see Table 28 and Table 29. However, as this is an exploratory study and to maintain the same structure the methodology proceeded without the exclusion of this construct.

As observed in Table 12, the results for age indicate that none of the path coefficient differences was statistically significant (all p-values above 0.212). Nonetheless, 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) - Figure 30, while for the age group >34, the only significantly influencing variable is PE (β=0.738; p-value=0.000) - Figure 31. As observed in Table 13 the results for gender, no statistically significant differences between path coefficients were noted (all p-values above 0.189). However, 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) - Figure 32. For males, also PE (β=0.709; p-value=0.000) and HM (β=0.139; p-value=0.036) effect UI - Figure 33. Finally, for previous robot experiences, as it can be seen in Table 14, again no significant differences were observed (all p-values above 0.181). However 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) - Figure 34, 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) - Figure 35. Similar results were achieved by the other three methodologies: PLS-MGA, Parametric and Welch-Satterthwait Tests (Table 30 of Appendix D).

Table 12: Permutation results for the moderation 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 13: Permutation results for the moderation 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 14: Permutation results for the moderation effect of robot related experiences

	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	0.358
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

Apart from the data gathered for the conceptual model, data from the third section the questionnaire was used for a brief analysis of the preferences of the participants, relative to the robots presented in the study. The third and final phase of the questionnaire yielded three statements to be answered for each of the four robots presented, in a seven-point Likert scale. The first statement is related to the Likability of the robot by the participants, the second refers to the robot's sociability or social skills and the third and last statement regards the robots' attractiveness. In addition to these three characteristics, a "share of heart" question was inserted in the questionnaire for participants to choose one of the four robots as their favourite.

By looking at the data, there were, unfortunately, 167 missing values, with some statements presenting more than 5% missing answers, though, as these answers are not part of the conceptual model, this was not considered an issue. Nonetheless, these values were surprising, and it is believed that most of these participants did not understand that it was intended for them to give an answer for each robot, instead, they assumed that it was to answer only to their favourite robot. Nonetheless, every valid answer was taken under consideration.

As it can be observed in Figure 21 or in Table 18 of Appendix B, the four social robots chosen for this study are quite different physically. Oshbot was included to represent a more

mechanical robot, *i.e.*, a mechanoid, as it does not even have a clear face, nor any human-like characteristics. Spencer represents the next level of mechanoid, by including a face, this gives the robot a more human appearance. Cruzr represents the bridge between mechanoids and humanoids, *i.e.,* the anthropomorphic robot. This robot has a pseudo-head incorporated in its torso and the fact that it includes arms, gives the robot a more animated look. Finally, Promobot represents the humanoid robot, with a clear head, torso and arms, this robot clearly has some human-like appearance, what sometimes is not good, *i.e.,* as it might enter the uncanny valley for some people. Thus, there is a mechanoid, a mechanoid with a human characteristic (head), an anthropomorphic robot and a humanoid.

Results show (Table 15) that the robot that was considered the most likable and attractive was Cruzr, with mean values of 4.04 and 4.28, respectively. In terms of sociability, Promobot surpassed Cruzr, though, by a very small margin. Results show a mean value of 3.84 for Cruzr and 3.85 for Promobot. The mechanoid robot (Oshbot) presented the lowest mean values of the four robots in all the statements. Thus, evaluating the mean values by the decimals, 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%), which was considered the most likable and attractive robot, and almost as highly evaluated as Promobot in terms of social skills. Immediately followed by Promobot (28.8%), which was rated the robot that elicits the best social skills and was the second best in the other two categories, then Spencer (22.6%), which was selected as third in every aspect. With Oshbot as the least selected robot as a participants' favourite (14.4%), considered to have the worst mean values when compared to the other three robots, as observed Figure 28.

Therefore, the results suggest that a mechanoid appearance is not the one that potential users want to see in a social robot, even the inclusion of a simple feature like a head (Spencer) or arms (Cruzr) makes a huge difference. Another conclusion suggested by these results is the fact that a humanoid robot is also not the best choice to consider when developing a social robot, as, the more the robot looks like a human, the more terrifying it can be for potential users, entering the uncanny valley. Thus, future social robot developers for public spaces should take this under consideration, and either attempt to develop a humanoid, though with caution for it not to be considered terrifying by some users, or develop anthropomorphic robots, that do not confuse or terrify users, by being different from the human-form. Notwithstanding, they must include some "living-being" features such as eye(s), mouth, arms or other.

Table 15: Sample Preferences - descriptive statistics

	N	Minimum	Maximum	Mean	Std. Deviation
LIK-Spencer	242	1	7	3,92	1,838
LIK-Promobot	243	1	7	3,93	1,790
LIK-Oshbot	240	1	7	3,81	1,901
LIK-Cruzr	241	1	7	**4,04**	1,855
SB-Spencer	244	1	7	3,54	1,662
SB-Promobot	240	1	7	**3,85**	1,794
SB-Oshbot	237	1	7	3,44	1,682
SB-Cruzr	237	1	7	3,84	1,753
ATR-Spencer	239	1	7	3,61	1,755
ATR-Promobot	240	1	7	4,13	1,788
ATR-Oshbot	240	1	7	3,49	1,677
ATR-Cruzr	238	1	7	**4,28**	1,847

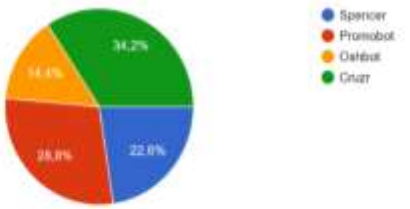

Figure 28: Results from the “Share of Heart” question

4.4. Results Discussion and Implications

Having thus completed all the phases of the proposed methodology, presented in Chapter 3, it is important to discuss the main outcomes and outline the implications resultant from the PLS-SEM analysis. Such implications, theoretical and practical, may confirm the results of other studies reviewed, and also serve as guidelines for social robot developers, thus, contributing to this research field.

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. In this research, as previously mention in Section 4.2.1., the option was to keep only the dimension “social influence”, which is the dimension used in the UTAUT2. Additionally, the inclusion of the dimension “image /status” in the model, basically does not change the results.

Also, still in the measurement model, 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 exclusion of the dimension SB, due to collinearity issues with SP and to a minor degree with HM. Nonetheless, the model was measured 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, the results of the model 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, as previously mentioned, the UTAUT is expected to explain around 70% of the variance of UI (Williams et al., 2015), and other UTAUT2 studies have also achieved very high values of the R^2 (77%) for UI (Cimperman, Makovec Brenčič, & Trkman, 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 studies, although, with different methodologies and approaches, in the context of public places, such as social robot acceptance (Kanda et al., 2009; Weiss et al., 2008, 2015), drone acceptance (Ramadan et al., 2016; Zhang et al., 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. 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, disproving 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), disproving 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, to our knowledge, no social robot acceptance studies presented similar results, thus, the finding in this study go against , Heerink et al. (2010), Graaf et al. (2017) and Giger & Piçarra (2018). While

one social robot studies 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 argued that, with larger sample all the effects of these dimensions would be significant. Nonetheless, the same cannot be said for the relevance of these effects, which, most likely, would represent similar low values.

Also, the results from an intermediate model, that includes SB as an antecedent of both HM and SP, are in line with the findings of Heerink et al. (2010), showing a strong positive influence.

The results from the MGA, revealed not a single statistically significant difference in the path coefficients of the compared groups: Male vs Female, Robot experience vs No robot experience and 18-34 years vs >34 years. Notwithstanding, results expressed that for males only performance expectancy was considered to influence intention to use; while for all the other groups, besides performance expectancy and hedonic motivation, there may be influence of facilitating conditions on people that had previous experience with robots, and of social presence in people that never had experience with robots, in the anticipated acceptance of social robots. Such results suggest that with a larger sample size, some of these differences might had been statistically significant. Therefore, it is suggested that future research should address this issue with a larger sample size.

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

This chapter comprises the main conclusions of the work performed, the limitations that were encountered throughout the dissertation and the suggestion of the future to be developed in this research field.

5.1. Main Conclusions

The evolution of technology over the last years, especially in what is related to the field of robotics, together with social needs and demand, has enabled the development of social robots. These are interactive robotic systems, that are able to communicate with people in unstructured environments, by eliciting social responses from humans and following predetermined social norms. These systems are expected to be successfully employed especially in the fields of Healthcare and Therapy, Education, Domestic, Workplaces and Public Spaces. Notwithstanding,

research shows that the simple presence of social robots, does not immediately increase user acceptance or willingness to interact with it (Kato *et al*., 2005).

As such, a review of the rise of robots towards social robots, and of social robots and their respective main application fields was performed. Also, the most prominent models used in prior technologies were characterized, as well as several social robot acceptance studies, and thus, it was possible to identify the most influencing variables of social robot acceptance, in light with the reviewed literature.

To address the challenge of social robot acceptance by humans, several studies have focused on extending social psychology behaviour models to the technology acceptance context, by influencing variables of acceptance and testing hypothesised influences between such variables, with indicators withdrawn from gathered data of questionnaires given to population samples. Such research framework has been increasingly applied in the field of social robotics, with studies covering the application fields of Healthcare and Therapy, Education, Domestic Environments and Workplace. However, in Public Spaces, there has not been developed nor applied a conceptual model of social robot acceptance. Thus, the present dissertation consists in a user-centred study that proposes and tests, with the PLS-SEM, a conceptual model, which was developed by grounding new variables to the UTAUT 2, to evaluate the anticipated acceptance of social robots in public spaces. This way, it attempts to contribute to the HRI field, and shorten the gap that is evident in the social robotic area, and even more scarce in the public spaces context. This is achieved by theoretically justifying and empirically proving the most influencing factors of the intention to use social, in this context, by a Portuguese sample of potential users and providing guidelines to future developers, resultant from the implications of the results attained.

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. Which 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 fun and use-oriented, thus ensuring, according to the results of this study, intention to use by future and actual users.

In addition, the added dimensions to the UTAUT2, SB and SP, both showed low mean values. SB was excluded from the model, while SP failed to show any effect in the variance of UI. This may be a reflection of the scepticism around the social characteristics of the robots, also noted in (Graaf et al., 2017). This which was manifested via comments, emphasizing that social actions should be only for humans, and that robots are not supposed to be taking the roles of humans in social actions, as the act of “talking to an electronic equipment is odd” and reflects in the “loss of quality on social life”. Nonetheless, it is argued that the better the social skills of a robot the easier it may induce HM on potential users, and thus, the influence of this variable on HM must be evaluated.

It is argued that the employment of social robots in public spaces might be the bridge to global social robot acceptance. As 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 provide facilitating conditions for mass usage, as introduction of social robots is made by organizations, 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 expectation. This study contributes to the understanding of users' anticipated acceptance of social robots in public spaces and provides recommendations for the design of communication, appearance and the factors to be taken into account as the most influencing of the acceptance, in this case, UI, thus easily meeting the expectations of users.

5.2. Limitations and Future Work

The present section presents few limitations that came across the development of this study, nonetheless, these were not serious enough to prevent reaching any results or accomplishing all the methodology steps. Such limitations are expected to serve as guidelines for future work, which is also outlined in this section.

The first limitation encountered was that due to the sampling method used, snowball sampling, results are not generalizable for the Portuguese population.

Another limitation is related to the fact that, 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). To deal with this limitation, based on Graaf et al. (2017) a definition of social robot was given in the questionnaire to the participants, along with a video that was developed following Giger & Piçarra (2018). Notwithstanding, future research could focus on conducting a similar study that includes a real-life experience with a social robot in a public scenario, which would cause the perceptions of participants to be more accurate, consequently increasing the reliability of the measurement and of the conceptual model.

In addition, also due to time and cost constraints, and to the previously mentioned limitation, limited resources, it was not possible to evaluate the "actual" acceptance of social robots by potential users, on the long-term. Therefore, the usage behaviour of social robots, which is a dimension of the UTAUT2, could not be measured. Instead, this study was conducted in the short-term, to evaluate the "anticipated" acceptance of social robots by potential users, measuring the main determinant of actual use, *i.e.*, UI, and its respective influencing dimensions. Hence, future studies are encouraged to develop long-term studies of social robot acceptance in public spaces, which could now be conducted in Portugal, given the introduction of social robots in Portugal (Lola - citizen's bureau since January 2019; Beltrão Coelho - Distributor of two social robots in Portugal).

The MGA revealed that none of the differences observed between the compared groups were found significant, what might have been a consequence of the small sample size of the groups. Therefore, it is encouraged that future research must address this issue and evaluate the moderating effects of age, gender and robot experience, with an appropriately larger sample. The group identification in future MGA research could also be performed by applying cluster analysis and other multivariate techniques.

Additionally, due to resource limitations, 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.

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 pertinent 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.

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APPENDIX A: Characterization of Previous Social Robot Acceptance Studies

Table 16: Characterization of the studies reviewed in section 2.3.2.

Article	Goal(s)	Application Field	Acceptance Models Based	Suggested Acceptance Variables	Experiment Design	Methods	Main Results/ Recommendations
Young et al. (2008)	Setting guidelines for future domestic robot developers and designers, attempting to: - Understand how people respond to domestic robots; - Explain their responsive behaviours.	Domestic	TRA; TPB; TAM; MATH;	**Influencing Variables:** - Safety; - Accessibility and Usability; - Practical Benefits; - Fun; - Social Pressures; - Status Gain; - Social Intelligence; **Perception Variables** - Previous Experience; - Media; - Personal Social Network; - Robot design.	—	—	The main results in this study are the identification and consequent application of the most significant variables found in the reviewed models to HRI, and the addition of some specific variables for the acceptance of domestic robots not included in any of the reviewed acceptance models
Broadbent et al. (2009)	Understanding how elders react and respond to SARs, highlighting the discovered influencing variables of such reactions and responses.	Healthcare for the Elderly	—	**User Variables:** - Age; - Needs; - Gender; - Experience with technology/ robots; - Cognitive Ability and Education; - Culture; - Role; **Robot Variables:** - Appearance; - Humanness; - Facial Dimensions and Expression; - Size; - Gender; - Personality; - Adaptability;	—	—	- Measures for the analysis of the acceptance of social robots must be defined; - Developers must clearly establish the robots design specifications; - Personification and customization of the robot's features, by users, influences its acceptance - Changes in the expectations affects the acceptance of social robots, since adapting expectations to the robot's capabilities may increase it.

Article	Goal(s)	Application Field	Acceptance Models Based	Suggested Acceptance Variables/ Constructs	Experiment Design	Methods	Main Results/ Recommendations
Heerink et al. (2010)	Building a model for the acceptance of SAR by the elderly	Healthcare for the Elderly	UTAUT;	- Intention to Use; - Attitude Towards Use; - Social Presence; - Perceived Usefulness; - Perceived Ease of Use; - Perceived Enjoyment; - Perceived Adaptability; - Perceived Sociability; - Facilitating Conditions; - Anxiety Towards Robots; - Social Influence; - Trust; - Actual Use;	**Experiment 1**. - Set-up: Two scenarios: one where the robot was remote controlled, and the other where the robot was autonomous, showing less social skills; - Robot: iCat; - Participants: 40 (20 in each set-up); 65-89 years old; **Experiment 2.** - Set-up: Participants were shown two videos of the robot, of approximately 5 minutes; One of an Adaptative version and one of a non-adaptative. - Robot: RoboCare - Participants: 88 - 45 watched the Adaptative and 43 the non-Adaptative version; **Experiment 3.** - Set-up: Interaction with a touch screen. - Robot: iCat - Participants: 30; 65-94 years old; **Experiment 4.** - Set-up: Menu-based interaction with a virtual social agent displayed on a screen; - Social Agent: Steffie - Participants: 30; 65-89 years old;	Model tested with SEM	- The model was sturdily verified, as all hypotheses were supported, with the exception in the influence of trust on intention to use; - The most important influences in this acceptance model of SAR for the elderly were Use as the determinant of acceptance, and Attitude Towards Use as a determinant of Intention to Use; - Results indicated a 59-79% explanatory power on the variance in intention to use and a 49-59% explanatory power in the variance of actual use.

Article	Goal(s)	Application Field	Acceptance Models Based	Suggested Acceptance Variables	Experiment Design	Methods	Main Results/ Recommendations
Klamer & Ben Allouch (2010)	Analysing HRI relationships-building and providing insight on how elder users perceive social robots for aging in place;	Healthcare for the Elderly in a domestic environment (Aging in Place)	TAM;	- Intention to use; - Usefulness; - Expectations; - Health; - Usefulness of Design; - Perceived enjoyment; - Perceived playfulness; - Trust; - Likeability; - Source credibility; - Appearance; - Novelty effect; - Subjective Norm; - Self-Identity; - Personal Interest in Technology	- Set-up: The robot was installed in the participants' homes for 10 days. The interactions were recorder by a camera. After this period, participants were interviewed; - Robot: Nabaztag - Participants: 3; 60, <50, 65 years old;	—	- Improvements in users' health and participants were not observed; - Participants did not find utility in using the robot; Nonetheless, the robot was considered easy to use overall, only with some technical or usage problems; - Hedonic factors were not found to influence acceptance of this social robot, in fact, they might only influence the development of human-robot relationship. - Subjective norm and self-identity appeared to have some influence in the acceptance;
Shin & Choo (2011)	Building an acceptance model for SIRs	SIR in general	TAM; UTAUT;	- Intention to Use; - Attitude Towards Use; - Social Presence; - Perceived Usefulness; - Perceived Adaptivity; - Perceived Sociability; - Perceived Enjoyment;	- Set-up: Participants assisted to a demonstration, by an instructor, on how to interact with three different social robots followed by a 20 to 30 minutes interaction with the robots; After the trial, participants answered a questionnaire; - Robots: Tito, PaPeRo and AIBO, - Participants: 210; >51 years old; 44% aged 21-30;	Model tested with SEM	- All Hypotheses were somewhat supported; - Results highlighted the influences of PU and PE in Intention, but not so much in Attitude Towards Use, - Also, social presence was observed to influence Attitude Towards Use. - Also, the constructs PA and PS have been observed to determine Attitude Towards Use;

Article	Goal(s)	Application Field	Acceptance Models Based	Suggested Acceptance Variables	Experiment Design	Methods	Main Results/ Recommendations
Graaf & Ben Allouch (2013)	Identifying the most influencing variables of social robot acceptance by means of an extensive literature review and verifying the validity of these identified variables, as well as investigating the respective relations between them;	Domestic	TPB;	Intention to Use; Attitudinal Beliefs: Utilitarian Variables Hedonic Variables Social Normative Beliefs: Control Beliefs: User Characteristics:	- Set-up: Simple conversation with the robot for a few minutes (5-10 minutes), followed by a questionnaire (20-30 minutes); - Robot: NAO - Participants: 60 students; 18 28 years old; 28 male participants and 32 female; German and Dutch, equally distributed;	-Cronbach alpha; -Spearman's correlation -Stepwise multiple regression; -T-test;	- Both Utilitarian and hedonic variables should be taken under consideration; - Major influences on the acceptance of social robots of the utilitarian variables: usefulness and adaptability, of the hedonic variables: enjoyment, sociability, companionship, and of perceived behavioural control;
Fridin & Belokopytov (2014)	Building a model for the acceptance of SAR in Education by preschool and elementary school teacher	Education	The Almere Model (UTAUT)	- Intention to Use; - Attitude Towards Use; - Social Presence; - Perceived Usefulness; - Perceived Enjoyment; - Perceived Adaptability; - Perceived Sociability; - Facilitating Conditions; - Anxiety Towards Robots; - Social Influence; - Trust;	- Set-up: Educational robotics workshop for preschool and elementary school teachers, where the robot approached attendants on a social manner, responding to the ones who answered it. Attendants were then asked to answer a UTAUT questionnaire. - Robot: NAO - Participants: Out of 36 teachers who interacted with NAO, only 18 answered the questionnaire; Aged 28 to 74;	- Cronbach alpha; - Pearson's correlation; - Linear regression;	- The constructs: facilitating conditions, social influence, social presence and trust, were not found reliable; - Consequently, only three hypotheses were tested, and all were confirmed, presenting good fallouts, especially in the influences of PU in intention to use and of perceived sociability in perceived enjoyment;

Article	Goal(s)	Application Field	Acceptance Models Based	Suggested Acceptance Variables	Experiment Design	Methods	Main Results/ Recommendations
Graaf et al. (2017)	Suggesting a conceptual model of social robot acceptance, with a sturdily theoretical foundation and test it on the Netherlands resorting to SEM	Domestic	TPB;	- Intention to Use; - Utilitarian Variables; - Hedonic Variables; - Personal Norms; - Social Norms; - Control Beliefs;	- Set-up: A questionnaire was sent to 4750 Dutch people as an invitation for voluntary participation; The questionnaire took about 15 minutes to complete; - Participants: 1162 valid questionnaires;	Model tested with SEM	- The most influencing factors for the acceptance of social robots are utility and usefulness. - The influences of hedonic factors and control beliefs in utilitarian factors were verified; - The influence of hedonic factors in control beliefs, was also confirmed - The influences of normative beliefs were not observed. - Early adoption is mostly influenced by control beliefs, while continuous actual use is majorly determined by attitudinal beliefs; - The sociability and companionship of social robots was predominantly judged as negative; - There is need for developers to clearly express the applicability of the robot and to build robot that are more useful, easy and pleasant to use;

Article	Goal(s)	Application Field	Acceptance Models Based	Suggested Acceptance Variables	Experiment Design	Methods	Main Results/ Recommendations
Giger & Piçarra (2018)	- Employ the MGB to social robot early adoption in the workplace; - Explore the roles that the robots' perceived warmth and perceived competence, as functions of the robot's appearance, have in intention to work with social robots; - Explore the roles that the variables BD and AE have in the prediction of intention to work with social robots.	Workplace	MGB (TPB)	- Intention to work; - Behavioural Desire; - Attitude Towards use; - Subjective Norm; - Perceived Behavioural Control; - Positive Anticipated Emotions - Negative Anticipated Emotions;	- Set-up: A video was presented to the participants of one out of three robots, chosen randomly. The video was around 2 minutes long and the content was equal for each robot, only differing on the appearance; Afterwards they they were asked to fill a questionnaire referent to the MGB. - Robots: Snackbot, ASIMO and Actroid DER 1 - Participants: 217; 18 to 66 years old; 130 female and 87 male;	Models tested with PLS-SEM	- The MGB presented good explained variance of Intention to Work with Social Robots; - BD and AE play an important role in this explained variance; - The effects of Perceived Warmth and Perceived Competence in intention were also noticed; - The effect of the robot's appearance was not confirmed;

APPENDIX B: Social Robots Characterization

Table 17: Characterization of the robot used in the studies reviewed in section 2.3.2.

Article	Robot		Description	Features	Developer	Stage	Website
Young et al. (2008)	Roomba		An autonomous mobile vacuum cleaner robot;	- Width: 35cm; Height: 9 cm; Weight:4 kg; - Intelligent sensors for navigation, furniture and cliff detection; - Dirt detection technology; - Self charging; Up to 90 min. of autonomy;	iRobot	Commercialized	irobot.com
Young et al. (2008)	RI-MAN		A personal assistive mobile humanoid robot built to for people with locomotion disabilities; Helps users move around their households, by carrying them; Hence, increasing their independence and consequent well-being; Follow some voice commands and even respond to them;	- Tactile sensors in the arms and torso to measure magnitude and location of force; - 6 joints and 6 motors in each arm; - Covered in soft material; - Two microphones with Reflectors for sound location; - Stereo cameras for visualization; - Two gas sensors that are able to distinguish several smells;	Riken	Prototype, replaced by RIBA*	rtc.nagoya.riken.jp
Heerink et al. (2010)	iCat		A user-interface cat-shaped robot, without an onboard processor, built for HRI research; The robot was designed to present different facial expressions, programmed in a platform called Open Platform for Personal Robotics (OPPR); Also, it can be used as a user interface for smart environments;	- Height: 38 cm; - 13 servo motors that control eyes, eyebrows, eyelids, lips, head and body; - Lights and touch sensors in both ears and paws; - 2 microphones; - Speaker; - Webcam;	Phillips	Discontinued	hitech-projects.com/icat
Heerink et al. (2010)	RoboCare		A mobile domestic Robot for the elderly, built to prevent harmful behaviours and monitor the user's behaviours alongside basic interaction skills; This robot was developed to explore the value of an embodied social agent in smart households;	- Topological path planning and reactive navigation for obstacle avoidance; - Scan-matching for vigorous localization. - Sonic speech recognition System; - Speech synthesis is done in the Lucia talking head; - Sensory subsystem to help locate the user; - Multi-agent coordination Infrastructure; - Daily activities monitoring;	ISTC CNR	Prototype	robocare.istc.cnr.it
Klamer & Ben Allouch (2010)	Nabaztag/Karotz		A rabbit-shaped Wi-Fi enabled ambient electronic device that is only able to understand pre-defined vocal commands; Although It has no learning ability or memory, it can be programmed as a robotic user interface for smart environments;	- Height: 23 cm; Weight: 418 g; - 5 LED lights; - Microphone; - Speaker; - Interchangeable ears with a motor in each; - RFID reader; - Wi-fi connected; - Text-to-speech synthesizer;	Violet	Discontinued	nabaztag.com
Shin & Choo (2011)	Tito		A mobile humanoid robot with a simple, appealing and predictable appearance, built to research HRI with children with low-functioning autism; Tito has a vocabulary of 25 words and a few pre-programmed movements and can be teleoperated;	- Height: 71 cm; - Washable clothes made of soft material; - Motors on the arms and on the neck; - Wireless microphone-camera; - Uses wheels to move; - Sound generating Device; - Approximately 1 hour of autonomy;	Université de Sherbrooke	Prototype	introlab.3it.usherbrooke.ca

Article	Robot		Description	Features	Developer	Stage	Website
Shin & Choo (2011)	PaPeRo		PaPeRo which means Partner-Type Personal Robot, is a communication robot that can recognize and interact with people, by visualizing and glazing, and by listening and speaking with them; Also, it can be a user interface for smart environments;	- Height: 38,5 cm; Width:28cm; Depth: 25 cm; Weight: 6,5 kg - 2 wheels for mobility; - 2 cameras, one in each eye; - Facial recognition system; - Heat sensor for Direction; - Ultrasonic sensor for proximity; - 2 microphones; - Speech recognition system; - Cloud based OS that can responds to users;	NEC Corp.	Commercialized	necplatforms.co.jp/solution/papero_i/
Shin & Choo (2011)	AIBO		A robotic pet that has a dog-like appearance and behaviour; It serves an entertainment purpose, yet it has been used in several HRI studies; Even though this robot is often perceived as a toy, it presents very advanced and sophisticated AI and hardware, which reflect on its price;	- Height: 29 cm; Width: 18 cm; Depth: 30 cm; Weight: 2.2 kg; - 2 OLED Displays for eyes; - Total of 22 axes for movement; - 4 microphones and a speaker; - One camera in the nose and another in the back; - 4G LTE internet connectivity; - Cloud based software that stores information, learns and shapes the robot's personality; - 2 hours of battery autonomy;	Sony	Commercialized	us.aibo.com
Graaf & Ben Allouch (2013): Fridin & Belokopytov (2014)	NAO		An autonomous, programmable humanoid robot that has been used for education and research purposes as well as for entertainment, and as an assistant robot by some companies; NAO is able to interact with people, talk, listen, express gestures and perform several tasks as walking, grabbing objects and rise after a fall;	- Height: 58 cm; Weight: 4,3 kg; - 25 degrees of freedom that allow his movements; - 2 cameras; - 7 touch sensors; Sonars and an inertial unit; - 4 Directional microphones; - Speakers; - Speech recognition system (20 Languages); - Uses an open, programmable software platform; - 90 minutes of autonomy;	SoftBank Robotics	Commercialized	softbankrobotics.com/emea/en/nao
Giger & Piçarra (2018)	SnackBot		A semi-autonomous mobile robot, that delivers snacks to students, faculty, and office workers at Carnegie Mellon University in his tray. The robot is also able to recognize people and objects, and even produce simpe verbal interactions. This robot was built as an ongoing platform for research.	- Height: 142 cm; - Bumpers, Sonars, one SICK and one URG lasers, for navigation; - Microphone and speakers; - Two different cameras; - 3 led displays in the mouth; - Two intel computers for data Processing;	Carnegie Mellon University	Prototype	cs.cmu.edu/~snackbot/about-public.html
Giger & Piçarra (2018)	ASIMO		ASIMO, which stands for Advanced Step in Innovative Mobility, is an autonomous humanoid robot with the ability to recognize moving objects, postures, gestures, sounds and faces, which allow him to interact with humans in a social level.	- Height: 130 cm; Weight: 54 kg; - Camera and led lights as eyes; - Microphone and speakers; - 6-axis foot area sensor; - Gyroscope & Acceleration Sensor; - Operating Control Unit; - Wireless Transmission Unit; - A total of 57 degrees of freedom (5 fingers; 13 DOF in each hand); - 1 hour of battery autonomy;	Honda	Discontinued	asimo.honda.com
Giger & Piçarra (2018)	Actroid - DER 1		A human-like robot that resembles an adult Japanese female. This robot has speech recognition software and can talk, blink, and mimic other basic human functions. Though, it is not autonomous, nor it has the ability to walk/move.	- Height: 158 cm; Weight: 30 kg; - Upper body includes between 42 and 47 DOF; - Microphones that filter unwanted sounds; - Speaker; - Speech recognition;	Osaka University	Commercialized	http://www.kokoro-dreams.co.jp

Table 18: Characterization of the robots used in the video;

Robot	Description	Features	Developer	Stage	Website
SPENCER 	This robot is the result of an EU-funded project involving six Universities and two industrial partners, being one of them KLM. The project started in April 2013 with 36 months of duration. This robot was developed to assist, inform and guide passengers in large and busy airports. Also, the robot has the particular task of guiding passengers of connecting flights conveniently and efficiently from their arrival gate to the passport control.	- Height:193 cm; Weight:250 Kg; - Dof: 2 in the head and 1 in each eye; - Maximal speed: 1.8 m/s; - 2 2D laser scanners, 1 3D laser scanner and tactile Bumpers; - 4 depth cameras and two cameras (stereo vision); - 17" touch screen, KLM boarding pass and passport reader, loudspeakers; - Two wheels, differential drive Kinematics; - Two high-performance laptops, three PCs and one motion controller (Real-time OS)	EU Project: Six Universities and Two Industrial partners	Project ended	spencer.eu
CRUZR 	A Customized, Cloud-Based, Intelligent Humanoid Service Robot. This is, between the robots used in this study the only one that has a distributor in Portugal, Beltrão Coelho. This high-tech robot has been developed to be deployed in a variety of industries, domestic and public environments. CRUZR is able to recognize faces and objects, move with notion around unstructured environments and communicate naturally, allow it to perform a wide range of tasks, from promotor, to welcoming host and even to museum guide or retail salesman.	- Height:119,5 cm; Width:52 cm; Depth: 51,6cm; Weight:45 Kg; - DoF:1 in the head 5 in each arm, 1 in each hand and 1 in the waist; - 3 Omni-wheels - Maximum speed: 1m/s; - 11.6" touch screen; - 13MP HD Camera; Facial Recognition system; - Speaker, microphones, speech recognition system; - 1 Depth perception camera in waist; - 1 Lidar, 6 Sonar sensors, 12 InfraRed sensors; - Android & ROS and Wi-Fi 2.4G/5G - 5 to 8 hours of battery life;	UBTECH	Commercialized	ubtrobot.com/pages/cruzr

Robot	Description	Features	Developer	Stage	Website
Promobot 	An autonomous robot presenting the latest technologies, that is able to recognize and remember a person, understand speech and communicate with natural language, move in unstructured environments, perform analytical reports and integrate any business platform. With such skills, this robot has been considered to be employed in airports, museums and exhibitions, retail and as an employee of any business.	- Height:156,5 cm; Width:78,2 cm; Depth:73 cm; - DoF: 2x7 in the arms, 2 in the head and 3 in the torso; - Camera with facial recognition System; - 1 Omnidirectional Microphone, 2 Speakers; Speech Synthesis and recognition systems; - 10.1" touch screen; - 16 Ultrasonic, 1 3D and 4 Touch Sensors; - 2 wheels and Mapping system for locomotion; - Up to 10 hours of battery life; - Up to 8 hours to recharge; - Open Linux System;	Promobot	Commercialized	promo-bot.ai
NAVii 	This autonomous retail service robot, NAVii or, depending on the branding OSHbot and LoweBot and has already been installed in a few retail surfaces in the USA. This robot was developed to help customers with simple questions, enabling more time for employees to focus on other tasks and to monitor inventory and analyse real-time data, helping the recognition of patterns or gaps that are essential to consider in business choices.	- Height: 152 cm; - 3 High-resolution Data Capture Cameras - Speech Recognition - Dual facing high-resolution monitors - Verbal Response, through speech synthesis system - Autonomous Navigation System; - 8 to 10 hours of battery life - 4 hours to recharge;	Fellow Robots	Commercialized	fellowrobots.com/navii-2/

APPENDIX C: Extended UTAUT 2 Questionnaire

TÉCNICO LISBOA

Utilização de Robôs Sociais em Espaços Públicos: Inquérito a potenciais utilizadores

Informação Pessoal

1. Sexo:

- Feminino
- Masculino

2. Idade:

- Menos de 18 anos
- 18-34 anos
- 35-54 anos
- 55-64 anos
- Mais de 64 anos

TÉCNICO LISBOA

Utilização de Robôs Sociais em Espaços Públicos: Inquérito a potenciais utilizadores

Intenção de Usar

Preencha as seguintes questões de acordo com a sua opinião em relação às afirmações apresentadas.

1. Se eu tiver a oportunidade de utilizar estes robôs, irei utilizá-los frequentemente no futuro.

	1	2	3	4	5	6	7	
Discordo Totalmente	○	○	○	○	○	○	○	Concordo Totalmente

2. Estou disposto a fazer um esforço para utilizar estes robôs.

	1	2	3	4	5	6	7	
Discordo Totalmente	○	○	○	○	○	○	○	Concordo Totalmente

3. Recomendo a utilização destes robôs a outras pessoas.

1 2 3 4 5 6 7

Preferências do potencial utilizador relativamente a cada robô mostrado no vídeo

Preencha as seguintes questões de acordo com a sua opinião em relação às afirmações apresentadas.

Caso necessite, reveja o vídeo.

1. Gostava de interagir com este robô social em espaços públicos.

	1 - Discordo Totalmente	2	3	4	5	6	7 - Concordo Totalmente
Spencer	○	○	○	○	○	○	○
Promobot	○	○	○	○	○	○	○
Oshbot	○	○	○	○	○	○	○
Cruzr	○	○	○	○	○	○	○

Figure 29: Final Questionnaire part I, part II and part III, from left to right

APPENDIX D: Synthesis Results

Table 19: Internal Consistency Reliability and AVE of the original model

	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
SB	0.799	0.794	0.505
SN	0.715	0.692	0.400
SP	0.901	0.902	0.756
UI	0.864	0.864	0.680

Table 20: Internal Consistency Reliability and AVE after the first changes

	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
SB	0.759	0.760	0.514
SN	0.833	0.833	0.715
SP	0.901	0.902	0.756
UI	0.864	0.864	0.680

Table 21: Cross-Loadings after the first changes

	EE	FC	HM	PE	SB	SN	SP	UI
EE01	**0.851**	0.631	0.206	0.293	0.223	0.335	0.116	0.339
EE02	**0.860**	0.625	0.256	0.407	0.215	0.329	0.125	0.407
EE03	**0.831**	0.627	0.285	0.285	0.268	0.328	0.081	0.311
FC01	0.675	**0.907**	0.319	0.307	0.208	0.371	0.104	0.366
FC02	0.664	**0.900**	0.292	0.305	0.150	0.399	0.035	0.341
FC03	0.663	**0.905**	0.343	0.328	0.216	0.391	0.095	0.367
FC04	0.689	**0.921**	0.349	0.305	0.266	0.341	0.130	0.386
HM01	0.293	0.370	**0.866**	0.578	0.467	0.500	0.291	0.627
HM02	0.246	0.290	**0.890**	0.641	0.606	0.547	0.403	0.649
HM03	0.236	0.297	**0.832**	0.557	0.541	0.565	0.358	0.569
HM04	0.166	0.192	**0.640**	0.425	0.418	0.425	0.208	0.504
PE01	0.310	0.282	0.550	**0.858**	0.351	0.485	0.234	0.851
PE02	0.335	0.311	0.585	**0.865**	0.370	0.470	0.247	0.812
PE03	0.336	0.327	0.558	**0.773**	0.511	0.435	0.396	0.639
PE04	0.253	0.161	0.486	**0.685**	0.370	0.471	0.293	0.644
SB02	0.242	0.217	0.438	0.411	**0.748**	0.363	0.503	0.455
SB03	0.113	0.049	0.443	0.375	**0.722**	0.235	0.650	0.365
SB04	0.243	0.235	0.472	0.279	**0.678**	0.325	0.453	0.356
SN01	0.377	0.383	0.521	0.505	0.335	**0.870**	0.199	0.530
SN02	0.281	0.313	0.543	0.476	0.392	**0.820**	0.291	0.457
SP01	0.157	0.132	0.375	0.361	0.659	0.300	**0.938**	0.353
SP02	0.083	0.040	0.316	0.297	0.665	0.209	**0.833**	0.299
SP03	0.085	0.085	0.333	0.280	0.629	0.238	**0.831**	0.319
UI01	0.338	0.343	0.619	0.820	0.409	0.515	0.300	**0.851**
UI02	0.292	0.333	0.604	0.702	0.478	0.466	0.343	**0.801**
UI03	0.398	0.319	0.569	0.773	0.473	0.465	0.281	**0.822**

Table 22: Cross-loadings of the final model

	EE	FC	HM	PE	SN	SP	UI
EE01	**0.852**	0.632	0.206	0.293	0.336	0.117	0.339
EE02	**0.867**	0.625	0.256	0.407	0.329	0.126	0.406
EE03	**0.825**	0.627	0.286	0.285	0.329	0.081	0.311
FC01	0.675	**0.907**	0.320	0.307	0.371	0.106	0.366
FC02	0.664	**0.901**	0.292	0.305	0.399	0.037	0.341
FC03	0.663	**0.905**	0.343	0.328	0.390	0.096	0.367
FC04	0.689	**0.919**	0.349	0.304	0.341	0.131	0.385
HM01	0.293	0.370	**0.880**	0.578	0.500	0.291	0.627
HM02	0.246	0.290	**0.885**	0.641	0.546	0.402	0.649
HM03	0.236	0.297	**0.831**	0.557	0.564	0.357	0.569
HM04	0.166	0.192	**0.630**	0.424	0.424	0.207	0.504
PE01	0.310	0.282	0.550	**0.858**	0.485	0.234	0.851
PE02	0.336	0.311	0.585	**0.865**	0.469	0.247	0.812
PE03	0.337	0.327	0.558	**0.771**	0.435	0.395	0.638
PE04	0.253	0.161	0.486	**0.685**	0.470	0.292	0.644
SN01	0.377	0.383	0.521	0.505	**0.881**	0.201	0.530
SN02	0.281	0.313	0.542	0.476	**0.810**	0.291	0.457
SP01	0.157	0.132	0.375	0.360	0.300	**0.993**	0.353
SP02	0.083	0.040	0.315	0.297	0.208	**0.782**	0.298
SP03	0.085	0.085	0.333	0.280	0.237	**0.822**	0.318
UI01	0.338	0.343	0.619	0.820	0.515	0.301	**0.863**
UI02	0.293	0.333	0.604	0.702	0.466	0.341	**0.793**
UI03	0.398	0.319	0.569	0.773	0.465	0.280	**0.817**

Table 23: Fornell-Larcker Criterion after the first changes

	EE	FC	HM	PE	SB	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				
SB	0.277	0.232	0.628	0.498	**0.717**			
SN	0.390	0.413	0.628	0.581	0.429	0.845		
SP	0.127	0.100	0.394	0.361	0.748	0.289	0.869	
UI	0.416	0.402	0.725	0.928	0.548	0.585	0.373	0.825

Table 24: HTMT values after the first changes

	EE	FC	HM	PE	SB	SN	SP	UI
EE								
FC	0.741							
HM	0.292	0.356						
PE	0.390	0.341	0.687					
SB	0.279	0.235	0.631	0.504				
SN	0.389	0.413	0.632	0.588	0.431			
SP	0.125	0.102	0.390	0.369	0.750	0.289		
UI	0.416	0.402	0.728	0.930	0.549	0.584	0.374	

Table 25: HTMT confidence intervals from bootstrapping after first changes

	Original Sample (O)	Sample Mean (M)	Bias	2.5%	97.5%
FC -> EE	0.741	0.740	-0.001	0.652	0.813
HM -> EE	0.292	0.291	-0.001	0.152	0.430
HM -> FC	0.356	0.354	-0.002	0.216	0.485
PE -> EE	0.390	0.389	0.000	0.259	0.516
PE -> FC	0.341	0.339	-0.002	0.202	0.481
PE -> HM	0.687	0.685	-0.002	0.583	0.779
SB -> EE	0.279	0.279	0.000	0.158	0.409
SB -> FC	0.235	0.243	0.008	0.136	0.346
SB -> HM	0.631	0.631	0.000	0.532	0.723
SB -> PE	0.504	0.504	0.000	0.389	0.609
SN -> EE	0.389	0.388	-0.002	0.245	0.530
SN -> FC	0.413	0.412	-0.001	0.292	0.527
SN -> HM	0.632	0.632	0.000	0.525	0.730
SN -> PE	0.588	0.587	-0.001	0.469	0.693
SN -> SB	0.431	0.432	0.001	0.294	0.548
SP -> EE	0.125	0.131	0.006	0.046	0.234
SP -> FC	0.102	0.111	0.009	0.048	0.195
SP -> HM	0.390	0.391	0.000	0.282	0.479
SP -> PE	0.369	0.370	0.001	0.259	0.465
SP -> SB	0.750	0.751	0.001	0.649	0.824
SP -> SN	0.289	0.290	0.001	0.160	0.413
UI -> EE	0.416	0.414	-0.001	0.288	0.539
UI -> FC	0.402	0.400	-0.002	0.270	0.528
UI -> HM	0.728	0.727	-0.001	0.632	0.806
UI -> PE	0.930	0.930	0.000	0.879	0.973
UI -> SB	0.549	0.550	0.001	0.429	0.649
UI -> SN	0.584	0.584	0.000	0.462	0.692
UI -> SP	0.374	0.375	0.002	0.256	0.477

Table 26: HTMT confidence intervals from bootstrapping for the final model

	Original Sample (O)	Sample Mean (M)	Bias	2.5%	97.5%
FC -> EE	0.741	0.741	0.000	0.659	0.825
HM -> EE	0.292	0.293	0.000	0.160	0.420
HM -> FC	0.356	0.351	-0.005	0.215	0.482
PE -> EE	0.390	0.386	-0.003	0.250	0.523
PE -> FC	0.341	0.335	-0.006	0.208	0.490
PE -> HM	0.687	0.683	-0.005	0.579	0.773
SN -> EE	0.389	0.387	-0.002	0.252	0.536
SN -> FC	0.413	0.409	-0.003	0.293	0.531
SN -> HM	0.632	0.631	-0.001	0.525	0.732
SN -> PE	0.588	0.581	-0.007	0.470	0.694
SP -> EE	0.125	0.130	0.005	0.048	0.237
SP -> FC	0.102	0.110	0.008	0.043	0.192
SP -> HM	0.390	0.393	0.003	0.284	0.488
SP -> PE	0.369	0.369	0.000	0.268	0.469
SP -> SN	0.289	0.290	0.001	0.155	0.399
UI -> EE	0.416	0.413	-0.002	0.291	0.542
UI -> FC	0.402	0.395	-0.008	0.269	0.528
UI -> HM	0.728	0.726	-0.002	0.639	0.805
UI -> PE	0.930	0.928	-0.002	0.882	0.973
UI -> SN	0.584	0.580	-0.004	0.476	0.696
UI -> SP	0.374	0.374	0.000	0.249	0.469

Table 27: MICOM results: Compositional Invariance.

	Age		Gender		Robot Experience	
	Corr.	5%	Corr.	5%	Corr.	5%
EE	1.000	0.992	1.000	0.995	0.999	0.995
FC	1.000	0.997	0.999	0.998	1.000	0.998
HM	0.999	0.997	1.000	0.997	1.000	0.997
PE	0.998	0.998	0.999	0.998	1.000	0.998
SN	1.000	0.997	1.000	0.997	0.996	0.998
SP	0.999	0.990	1.000	0.993	0.999	0.993
UI	1.000	0.999	1.000	0.999	1.000	0.999

Table 28: MICOM results: Composite equality (Mean).

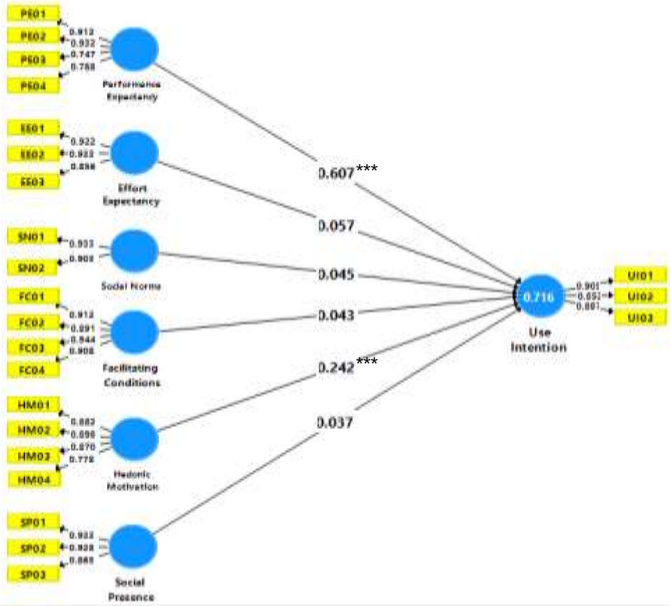
	Age				Gender				Robot Experience			
	Mean Dif.	2.5%	97.5%	p-value	Mean Dif	2.5%	97.5%	p-value	Mean Dif	2.5%	97.5%	p-value
EE	0.137	-0.257	0.276	0.325	-0.182	-0.235	0.242	0.152	-0.38	-0.237	0.238	-
FC	0.246	-0.271	0.270	0.071	-0.382	-0.246	0.240	-	-0.417	-0.251	0.238	-
HM	0.106	-0.267	0.274	0.467	0.127	-0.249	0.224	0.294	0.012	-0.254	0.245	0.929
PE	-0.128	-0.282	0.259	0.346	0.045	-0.252	0.220	0.703	-0.069	-0.244	0.249	0.576
SN	0.060	-0.274	0.255	0.665	-0.249	-0.247	0.238	0.044	0.120	-0.245	0.246	0.367
SP	-0.063	-0.27	0.280	0.649	0.117	-0.24	0.233	0.367	-0.017	-0.231	0.247	0.903
UI	-0.263	-0.271	0.270	0.060	0.095	-0.244	0.218	0.416	-0.018	-0.256	0.259	0.884

Table 29: MICOM results: Composite equality (Variance).

	Age				Gender				Robot Experience			
	Var. Dif.	2.5%	97.5%	p-value	Var. Dif	2.5%	97.5%	p-value	Var. Dif	2.5%	97.5%	p-value
EE	-0,031	-0,444	0.478	0.885	-0,017	-0,442	0.428	0.944	0.185	-0,431	0.397	0.393
FC	-0,147	-0,455	0.550	0.548	0.154	-0,445	0.421	0.487	0.242	-0,448	0.400	0.274
HM	-0,1	-0,328	0.383	0.582	-0,134	-0,318	0.299	0.377	0.032	-0,328	0.306	0.833
PE	0.214	-0,373	0.378	0.242	-0,007	-0,336	0.337	0.963	-0,092	-0,327	0.313	0.586
SN	0.207	-0,393	0.405	0.322	0.416	-0,363	0.361	0.023	-0,094	-0,359	0.356	0.590
SP	0.104	-0,475	0.555	0.696	0.149	-0,428	0.437	0.501	-0,211	-0,45	0.439	0.331
UI	0.209	-0,366	0.378	0.250	-0,143	-0,338	0.338	0.422	0.080	-0,314	0.333	0.619

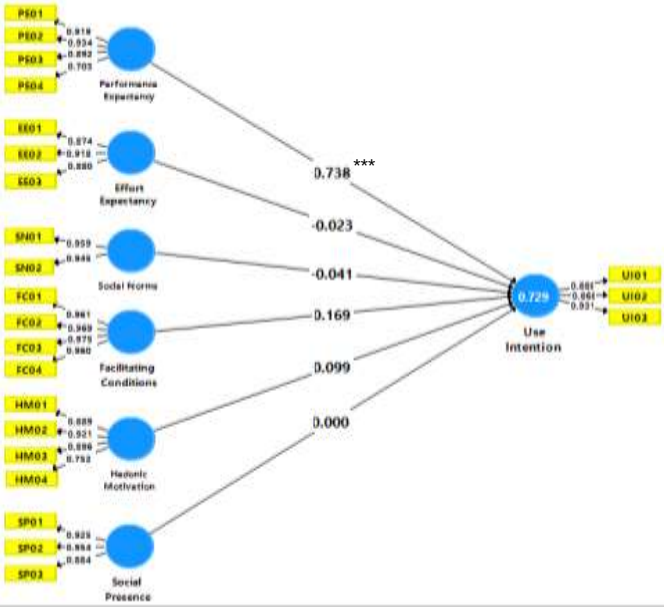
Table 30: Results for the Parametric and Welch-Satterthwait Tests and for the PLS-MGA.

	Age				Gender				Robot Experience			
	Dif.	p Par.	p WS	p MGA	Dif.	p Par.	p WS	p MGA	Dif.	p Par.	p WS	p MGA
EE -> UI	0,080	0,525	0,569	0,279	0,012	0,921	0,922	0,469	0,055	0,617	0,616	0,313
FC -> UI	0,126	0,315	0,365	0,819	0,070	0,560	0,572	0,277	0,110	0,312	0,311	0,846
HM -> UI	0,142	0,178	0,198	0,097	0,073	0,482	0,486	0,244	0,047	0,636	0,635	0,320
PE -> UI	0,131	0,171	0,169	0,918	0,124	0,170	0,170	0,915	0,100	0,260	0,260	0,871
SN -> UI	0,086	0,371	0,356	0,178	0,029	0,740	0,740	0,374	0,015	0,869	0,868	0,567
SP -> UI	0,036	0,680	0,660	0,326	0,016	0,851	0,854	0,571	0,114	0,174	0,174	0,088



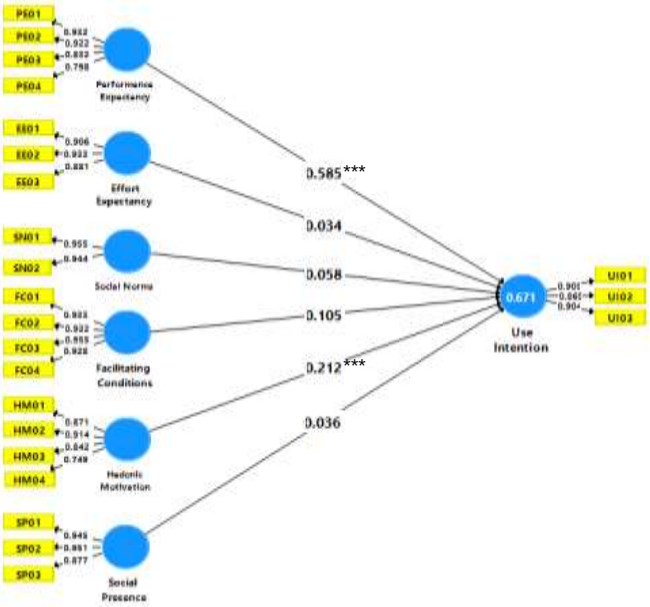
*** p ≤ 0.01
** p ≤ 0.05
* p ≤ 0.1

Figure 30: PLS Results for the age group 18-34 years.



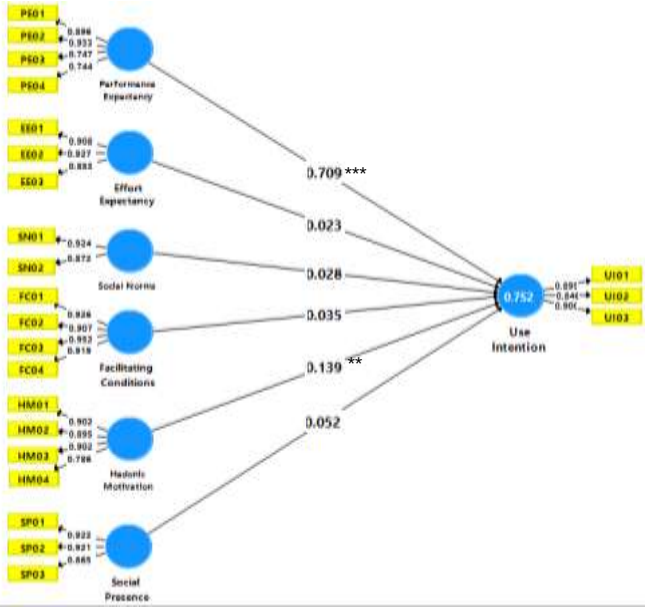
*** p ≤ 0.01
** p ≤ 0.05
* p ≤ 0.1

Figure 31: PLS Results for the age group >34 years.



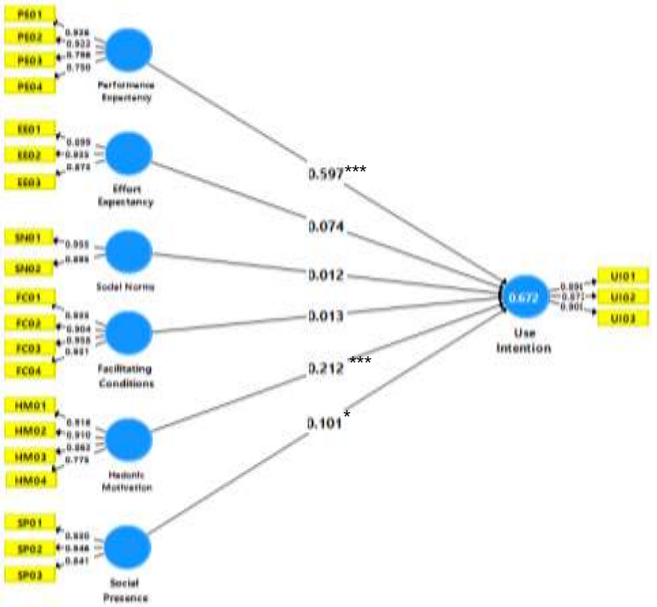
*** p ≤ 0.01
** p ≤ 0.05
* p ≤ 0.1

Figure 32: PLS Results for females.



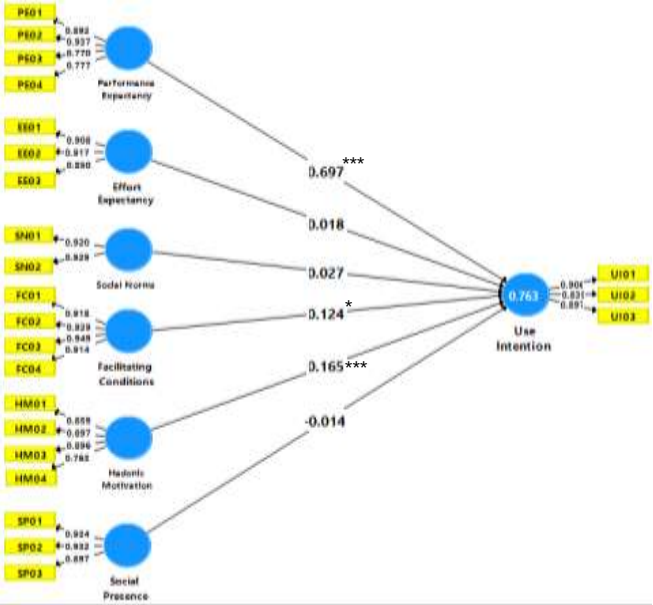
*** p ≤ 0.01
** p ≤ 0.05
* p ≤ 0.1

Figure 33: PLS Results for males.



*** p ≤ 0.01
** p ≤ 0.05
* p ≤ 0.1

Figure 34: PLS Results for people without previous robot experiences.



*** p ≤ 0.01
** p ≤ 0.05
* p ≤ 0.1

Figure 35: PLS Results for people with previous robot experiences.