Adapting Robot Behaviour in Smart Homes: A Different Approach Using Personas

by

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Abstract

A challenge in Human-Robot Interaction is tailoring the social skills of robot companions to match those expected by individual humans during their first encounter. Currently, large amounts of user data are needed to configure robot companions with these skills. This creates the need of running long-term Human-Robot Interaction studies in domestic environments. A new approach using personas is explored to alleviate this arduous data collection task without compromising the level of interaction currently shown by robot companions.

The personas technique was created by Alan Cooper in 1999 as a tool to define user archetypes of a system in order to reduce the involvement of real users during the development process of a target system. This technique has proven beneficial in Human-Computer Interaction for years. Therefore, similar benefits could be expected when applying personas to Human-Robot Interaction. Our novel approach defines personas as the key component of a computational behaviour model used to adapt robot companions to individual user's needs. This approach reduces the amount of user data that must be collected before a Human-Robot Interaction study, by associating new users to pre-defined personas that adapt the robot behaviours through their integration with the computational behaviour model. At the same time that the current robot social interaction level expected by humans during the first encounter is preserved.

The University of Hertfordshire Robot House provided the naturalistic domestic environment for the investigation. After incorporating a new module, an Activity Recognition System, to increase the overall context-awareness of the system, a computational behaviour model will be defined through an iterative research process. The initial definition of the model was evolved after each experiment based on the

findings. Two successive studies investigated personas and determined the steps to follow for their integration into the targeted model. The final model presented was defined from users' preferences and needs when interacting with a robot companion during activities of daily living at home. The main challenge was identifying the variables that match users to personas in our model. This approach open a new discussion in the Human-Robot Interaction field to define tools that help reduce the amount of user data requiring collection prior to the first interaction with a robot companion in a domestic environment.

We conclude that modelling people's preferences when interacting with robot companions is a challenging approach. Integrating the Human-Computer Interaction technique into a computational behaviour model for Human-Robot Interaction studies was more difficult than anticipated. This investigation shows the advantages and disadvantages of introducing this technique into Human-Robot Interaction, and explores the challenges in defining a personas-based computational behaviour model. The continuous learning process experienced helps clarify the steps that other researchers in the field should follow when investigating a similar approach. Some interesting outcomes and trends were also found among users' data, which encourage the belief that the personas technique can be further developed to tackle some of the current difficulties highlighted in the Human-Robot Interaction literature.

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Chapter 1

Introduction

1.1 Introduction

In the near future, robot companions will be part of our daily life trying to help with domestic tasks and taking care of us when needed. However, before this becomes a reality, important issues need to be addressed in the Human-Robot Interaction (HRI) field in order to achieve social robots capable of interacting with humans in a similar way to which humans interact with each other (Breazeal et al. 2016). One of the biggest challenges in this field is to endow robot companions with those social capabilities needed to interact with a person during a continuous period of time (Breazeal 2004). These skills can be enhanced by using robot's own sensors or external sensory systems installed around the experimental environment, so robots could be aware of the contextual information. The incorporation of these capabilities looks to improve the interaction and the robot companions acceptance by humans. People have expectations when first encountering a robot, especially in domestic environments, where the ability to socialise and communicate in a human-like way is a fundamental feature to incorporate in order to achieve the desired level of interaction expected by humans.

Researchers in the HRI field are focused on understanding how humans interact with robots in the different environments where robots could be integrated in the near future, e.g. (Breazeal 2004) (Dautenhahn 2007) (Cortellessa et al. 2008). The incorporation of mechanisms to improve robot responses during social interactions seems a key part of this integration, as robots will be expected to adapt their behaviours as humans would (Fong et al. 2003a). In the area of assistive robotics, particularly in domestic environments where robots will become part of people's lives, these social skills must be incorporated during early stages of the development process. This will make possible to develop socially accepted robot companions for these environments. In order to achieve that, robots should be endowed with capabilities that make them aware of user behaviours and activities performed in the environment (Duque et al. 2013a). In addition, robot companions must also comply with certain social rules in order to adapt themselves to the environment and the users' characteristics.

Several definitions of social robots can be found in the literature, but the one proposed by Bartneck & Forlizzi seems the most relevant to the research purposes (Bartneck & Forlizzi 2004). The author defines a social robot as "*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*" (Bartneck 2004, p. 592). This means that user expectations and the degree to which researchers are able to fulfil these are fundamental in the HRI field, in particular during long-term interactions such as in domestic environments. Also other definitions should be considered, for instance the one proposed by Breazeal, who defines social robots as those who pro-actively engage with humans in order to benefit humans and also benefit themselves (Breazeal 2003). Another term is introduced by Fong et al. who describes socially interactive robots as the group of robots for which social interaction is the key role (Fong et al. 2003a). In addition, they should show a certain degree of adaptability to be able to interact with a variety of participants. Finally, the definition of Dautenhahn could be presented, who defined social robots as those that express emotions, communicate using high-level dialogue, recognise other agents, maintain social interaction or exhibit distinctive personality (Dautenhahn 2007). Based on these definitions, a common aspect among them could be extracted: the need for adaptation to humans, i.e. to exhibit distinctive behaviours in reaction to humans' needs.

Inside the HRI field, several areas of study are found. This research is located inside social robotics and, in particularly, social interactive robotics and social assistive robotics. The latter is directly related to the investigation of robots in smart environments such as the University of Hertfordshire (UH) Robot House. This is a naturalistic environment utilised by the *Adaptive Systems Research Group* to perform a variety of HRI and interrelate projects e.g. (*COGNIRON: The Cognitive Robot Companion* 2004-2007) (*LIREC: Living with Robots and Interactive Companions* 2007-2013) (*ACCOMPANY: Acceptable robotiCs COMPanions for AgeiNg Years* 2011-2014). These kinds of environments give the possibility of running experiments in a controlled environment to collect and analyse data repeatedly. This allows researchers to identify user preferences and the robot behaviours to be implemented in order to adapt the system to future HRI participants. However, the recruitment task for HRI studies and the performance of long-term experiments in order to collect user data is a well-known issue in the field. In this context, a different approach to achieve the robot behaviour adaptation was investigated. In addition, this research will contribute to reduce the current burden put on participants during the development and training stages of an HRI system.

The use of data-driven approaches, whereby a system collects data on people's behaviour and daily activities, is followed by the identification of patterns to be used in order to adapt the system to each individual. Recognising typical user behaviours and preferences in a home environment usually requires large datasets to create accurate systems (Van Kasteren et al. 2008), and many difficulties could be found while recruiting participants for these kinds of experiments (Bien et al. 2008). This research focuses on a solution to cope with the current problem and simplified the process followed to achieve social robots without compromising the robot social skills shown during HRI studies. In addition, the research tries to bridge the gap between the design of HRI studies and implementation of social skills in the companion in order to make them accepted by humans. The personas technique (Cooper 1999), successfully used in the Human-Computer Interaction (HCI) field, and its integration into a computational behaviour model for HRI studies, may positively contribute to achieve this research goals.

1.2 Motivation and Goals

According to Fong et al. "Regardless of function, building a socially interactive robot requires considering the human in the loop: as a designer, as an observer, and as interaction partner" (Fong 2003, p. 146). In the field of HRI, users could be required during the whole design and development process of a socially interactive system. Moreover, several iterations of the process could be performed before achieving the desired performance of the system and the robot social capabilities expected by humans during the interaction. For instance, the current social interaction shown by the UH Robot House robot companions were achieved across multiple investigations and data collected during the last decade, e.g. (*COGNIRON: The Cognitive Robot Companion* 2004-2007) (*LIREC: Living with Robots and Interactive Companions* 2007-2013) (*ACCOMPANY: Acceptable robotiCs COMPanions for AgeiNg Years* 2011-2014). In HRI studies, robot acceptance relies on the capacity of the system to react appropriately to the situation presented based on the user expectations (Breazeal 2004). The need for data and the difficulties obtaining this could be seen as an opportunity to investigate a different approach in order to reduce the time currently required to collect data and configure the system.

The investigation of a different approach to cope with the problem aforementioned, in particular in domestic environments, will contribute to reduce some of the current difficulties pointed out in the field of HRI. For instance, the reduction in the time taken by participants during the development process of the system seems something evident to be addressed to benefit the HRI field. It should bear in mind that each robot feature presented during the interaction have to be tested and trained individual for each user when adapting the system to participants' preferences and needs. A few year ago, Bien et al. already remarked the difficulties of recruiting participants for HRI studies (Bien et al. 2008). In addition, the long-term experiments performed in the field will require these participants to attend the experimental place several times over a few weeks or months period, e.g. (Derbinsky et al. 2013) (Leite et al. 2013) (Syrdal et al. 2014) (Koay et al. 2016). Long-term experiments are preferable over short-term by researchers as they offer the opportunity of collecting a bigger amount of data, nevertheless, there is not an easy way of engaging people for a long period of time. The problem identified motivate the investigation of a general solution that improves the current process followed during the development of the system. Robot companions are expected to show a certain level of social interaction to avoid user dissatisfaction during the interaction. The approach to be investigated will still keep the current state-of-art regarding robot social capabilities as other systems do after collecting user data through several studies. However, once the computational behaviour model is defined, the time used by HRI participants to train a socially interactive system should be drastically reduced. The investigation of the personas technique as part of this computational behaviour model will determine the degree in which this reduction can be achieved and the novel approach be successfully applied in the future.

Breazeal highlighted that HCI-like studies could be applied to the area of HRI in order to understand the way people interact with robots (Breazeal 2004). Despite this idea being suggested more than a decade ago, little research has been done, to the best of my knowledge, about the benefits of integrating the personas technique into a computational behaviour model to modify robot companion behaviours in a domestic environment. As aforementioned, this technique has been widely used in the area of HCI and its success has been proven by several researchers, e.g. (Chen et al. 2009) (Chen et al. 2011) (Nivala et al. 2011) (Pruitt & Grudin 2003). The use of personas provides a valuable set of users archetypes to guide the design and definition process of the socially interactive system based on users characteristics and needs (Cooper et al. 2007). This defines the basis to determine the *first encounter* between users and robot companions without requiring HRI participants to perform long-term experiments to train the system. Domestic environments are expected to be a common place to find robots and humans cohabiting in the near future. The robots acceptance in these environments will be a key part to their success and their integration in the future society.

The incorporation of the personas technique into the computational behaviour model should help decreasing the amount of time demand on HRI participants when developing a socially interactive system. The results from this investigation are expected to supply a different methodology to reduce some of the steps followed during the development process. The personas-based model will guide the definition of robot behaviours to adapt the system to users' needs and preferences at the first encounter. This computational behaviour model will be responsible for matching users to the pre-defined personas of the system. Each of these personas will have an associated robot behaviour to be applied during the interaction. An example of the model will be described based on the research outcomes at the end of this dissertation. The adaptation of robot behaviours to participants' personality has already been investigated in the field of HRI. As Tapus and Matarić proved, the adaptation of robot behaviours to user personality increased the patient task performance where robot and user personality were matched (Tapus & Matarić 2006). Personas depict users archetypes of a system and defines their personality and their needs interacting with the environment. By finding the relation between users and pre-defined personas, it should be possible to identify the users' characteristics, and thus, adapt robot companions behaviours and responses to the environment accordingly.

Bearing in mind the difficulties pointed out when recruiting HRI studies participants, the integration of the personas technique as part of a computational behaviour model will positively contribute the HRI field. The model will guide the creation of socially acceptable behaviours for robot companions in smart homes. As mentioned by Breazeal, the success of social robots does not just rely on their utility towards users, but also on their abilities to respond and interact with them in a natural and intuitive way (Breazeal 2004). Consequently, the use of personas in HRI studies could constitute an efficient way of developing the characteristics and responses that a robot companion is expected to show when first encountering a certain type of user. In addition, the personas-based model, once defined, would help reduce the number of hours currently required to collect users' data and adapt the system prior to the interaction with humans. At the end of this research, the advantages and disadvantages of this approach will be stated and presented to the HRI community. The definition of this personas-based computational behaviour model will contribute to bridge the gap between the user and the robot when first interacting. This achievement will positively contribute to future research over social interactive systems inside the HRI field.

1.3 Research Questions

Some of the computational behaviour model components are inspired by previous HRI models and frameworks already researched in the field (Duque et al. 2013b). The success defining this model is expected to reduce users' data collection prior to the interaction. The model will determine the robot social skills to match users' characteristics when first interacting, so robot companions can still be configured to suit users' needs and preferences. The success of this investigation will directly benefit and improve the current development process of socially interactive systems. To the best of my knowledge, only a few HRI studies have introduced the personas technique in the HRI field, but none of them investigated the technique as part of a computational behaviour model for robot companions in domestic environments (see Section 2.6). This research investigates personas as the core component of a computation behaviour model to adapt robot behaviours to users' needs during the *first encounter*.

An initial definition of the model, built on the results and experiences from previous European research projects in our department (*COGNIRON: The Cognitive Robot Companion* 2004-2007) (*LIREC: Living with Robots and Interactive Companions* 2007-2013), will be evolved after each iteration of the research process and based on the findings. At the end of the evaluation process, a set of significant variables will be defined in order to match users and the pre-defined personas created on the system. By identifying the type of user that this system is interacting with, the set of robot behaviours could be determine to best match the user's expectations during the interaction. In order to evaluate the proposed approach, the UH Robot House will be used, a naturalistic environment to perform HRI studies. Our department is still using this environment for the latest studies performed, e.g. (Koay et al. 2013) (Salem et al. 2015) (Koay et al. 2016). This has always been an ideal scenario to investigate HRI studies, therefore it will be used to explore this novel approach using personas and discover the benefits and the difficulties of incorporating the concept into the computational behaviour model targeted. Following the set of research questions defined to guide the direction of this research:

1. *RQ1*: Which system architecture should we define in order to create a computational system able to automatically adapt a robot companion's behaviour to users based on their needs?

2. *RQ2*: Would people with a similar background, characteristics and personality prefer the same robot behaviours and responses during the interaction?

3. *RQ3*: Which are the most significant variables found that could help identifying the users' preferences and needs so we are able to adapt the system appropriately?

4. *RQ4*: Which are the advantages and disadvantages of integrating the concept of personas into the development process of a computational behaviour model for robot companions in smart homes?

5. *RQ5*: Which robot features should be adapted based on the research outcomes investigated during this dissertation?

1.4 Methodology

For the purpose of this research, two development methodologies have been considered, the *Incremental* and the *Iterative* methodology (Larman & Basili 2003). The first one divides the development process into pieces of work that is developed and added incrementally to the whole system. The second approach considers an initial piece of the system that is evaluated and improved through the consecutive iterations over the whole process of development. An initial model will be defined and expanded based on the research outcomes. Therefore, the iterative methodology (Arkin 1998) (Larman 2004) best suits this research needs to effectively carry out the personas investigation, see Figure 1.1. This methodology will help to better understand how the personas technique could be integrated into the computational behaviour model in order to modify robot companion behaviours based on the user's characteristics. The first steps will be to define an initial set of personas and an initial behaviour model to successively iterate over those and modify the system based on the findings of each of the studies to be performed. During the investigation, the problems and improvements for the initial model will be identified to better match user's needs and preferences in future stages of the research. This capability of using previous outcomes to guide the next stage of the investigation will be crucial to succeed on the research approach proposed in this dissertation.

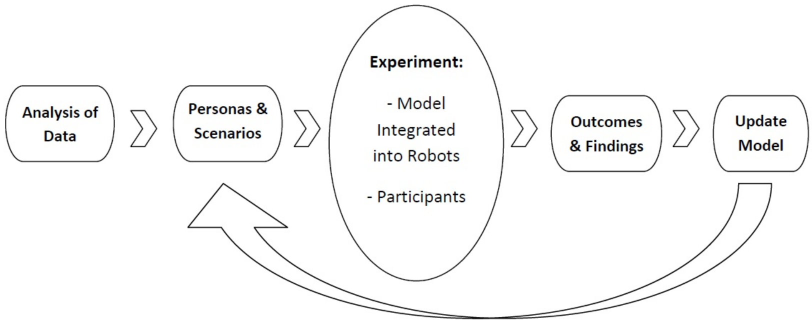

Figure 1.1: Iterative Methodology used to investigate the computational behavioural model for robot companions in smart homes

In order to adapt the experimental environment to the research requirements, a human activity recognition module was required in order to enhance the capabilities shown by the system during the interaction. One of the first steps towards social robots is to endow them with the capability of sensing and understanding the environment where they are operating in. Therefore, having the possibility of knowing about users' current activities during the interaction, will allow robots to adapt their behaviour to the current status of the system. As a result, a knowledge-driven Activity Recognition System (ARS) was developed, integrated and evaluated into the UH Robot House. The *Experiment 1*, see Table 1.1, was used for the evaluation process as detailed in Chapter 3. This system helped to increase the social skills already shown by the robot companions at the house. This task was considered a priority before investigating the personas technique. At the same time, the experiment conducted during evaluation of the human activity recognition system was used to collect useful data for the definition of personas and to understand the requirements of potential users of the future system.

Experniment Name	**Description**	**Chapter**
Experiment 1	Evaluating the Activity Recognition System created	Chapter 3
Experiment 2	Investigation the Computational Behaviour Model based on Pesonas - First Iteration	Chapter 5
Experiment 3	Investigation the Computational Behaviour Model based on Pesonas - Second Iteration	Chapter 6

Table 1.1: Experiments performed during this research, short description and chapter where explained

In order to start the personas investigation, some of the information gathered during previous European projects at the UH Robot House (Dautenhahn et al. 2005) and data collected during the *Experiment 1*, were used to define the first set of personas in the behavioural model. Each persona characterises a group of end users of the system, in this particular case, people sharing the same space with a robot companion at home. The ability to associate each individual with a persona in order to adapt the robot's behaviour to the model's suggestion, will be a valuable feature to reduce the time and effort when identifying user preferences through the collection of data during several studies. Two iterations, *Experiment 2* and *Experiment 3*, were performed to investigate this novel approach and following the iterative methodology presented (Fig 1.1). Before these iterations, an initial definition of the personas, the user variables to be used to match users and robot behaviours and the initial model were defined in Chapter 4.

The resources to be used throughout the research includes all hardware located at the Robot House and necessary to run HRI studies using Sunflower, a companion created as part of the LIREC project (*LIREC: Living with Robots and Interactive Companions* 2007-2013). As mentioned earlier, the ARS was developed and integrated into the previous network system. In addition, other applications were developed in order to run the experiments. For instance, a new Graphical User Interface (GUI) was develop to establish the communication between the user and the robot throughout the experiment as well as other layers necessary to integrate some components into the system developed as part of the ACCOMPANY Project (*ACCOMPANY: Acceptable robotiCs COMPanions for AgeiNg Years* 2011-2014). This methodology allowed other members from our department to avoid incompatibility issues between the new system being created as part of the European project, and the components installed during the development stages of this investigation.

1.5 Publication List

During my research period at the Adaptive Systems Department at the University of Hertfordshire, I have written three research papers, two conferences and one journal (this latter was in preparation at the time this dissertation was submitted), as main author. The first complete draft for each paper was completed by the author, and after revision and approval from the supervisors, these were submitted for publication. In addition, my supervisors have guided and supported me during the design, development and evaluation process of the studies presented in this dissertation.

Grammatical convention

The royal "we", "us" or "our" is used in this thesis to always refer to the author of this thesis, unless otherwise explicitly stated.

Publications

The following lists the publication and other contribution of work done during this research. The author's published articles can be found in the Appendix A.

- Ismael Duque, Kerstin Dautenhahn, Kheng Lee Koay, Ian Willcock, Bruce Christianson: Knowledge-Driven User Activity Recognition for a Smart House. Development and Validation of a Generic and Low-Cost, Resource-Efficient System. In ACHI 2013, The Sixth International Conference on Advances in Computer-Human Interactions, pages 141-146, 2013. [Chapter 3 contribution] - (Duque et al. 2013a).
- Ismael Duque, Kerstin Dautenhahn, Kheng Lee Koay, Bruce Christianson, Ian Willcock: A Different Approach of Using Personas in Human-Robot Interaction: Integrating Personas as Computational Model to Modify Robot Companions' Behaviour. RO-MAN, IEEE 2013, pages 424-429. [Chapter 4 contribution] - (Duque et al. 2013b).
- Ismael Duque, Kerstin Dautenhahn, Kheng Lee Koay, Bruce Christianson, Ian Willcock: Exploring Personas in Human-Robot Interaction Studies. Chal-

lenges in Developing a Computational Behaviour Model for HRI - Journal Paper [In preparation - Based on Chapter 5].

Other Contributions

- Collaboration with the visitor researcher, Nate Derbinsky, for the preparation of the following article: Nate Derbinsky, Wan Ching Ho, Ismael Duque, Joe Saunders, Kerstin Dautenhahn. Resource-Efficient Methods for Feasibility Studies of Scenarios for Long-Term HRI Studies. ACHI 2013, The Sixth International Conference on Advances in Computer-Human Interactions: 95-100 - (Derbinsky et al. 2013)
- Collaboration on the preparation of the following study: Hagen Lehmann, Michael L. Walters, Anna Dumitriu, Alex May, Kheng Lee Koay, Joan Saez-Pons, Dag Sverre Syrdal, Luke Jai Wood, Joe Saunders, Nathan Burke, Ismael Duque-Garcia, Bruce Christianson, Kerstin Dautenhahn: Artists as HRI Pioneers: A Creative Approach to Developing Novel Interactions for Living with Robots. ICSR 2013: 402-411 - (Lehmann et al. 2013).
- The data collected during the evaluation process of the activity recognition system (Duque et al. 2013a) has been extensively used in the following research: Joe Saunders, Dag Sverre Syrdal, Kheng Lee Koay, Nathan Burke, and Kerstin Dautenhahn. “Teach Me - Show Me” - End-User Personalization of a Smart Home and Companion Robot. IEEE Transactions on Human-Machine Systems, 46(1):27-40, Feb 2016 - (Saunders et al. 2016).

1.6 Thesis Content Overview

This chapter has introduced the main area of interest and highlighted the research questions that will guide the rest of this investigation. In addition, the main motivations and the methodology followed have been described in order to achieve the final research target. The subsequent chapters are described as follows:

- **Chapter 2 -** This chapter lists the relevant literature related to the research. The main points covered are the relation between the HCI and the HRI fields, and how the success of the personas technique inside the HCI area could be translated to the HRI field. In addition, the current challenges in HRI are pointed out and how this research contributes to partially solve these problems. Finally, the chapter presents the research questions and the way in which they will be addressed during this dissertation.

- **Chapter 3 -** This chapter presents the creation, development and evaluation process of the ARS system integrated into the UH Robot House. This chapter content is supported by the published article (Duque et al. 2013a). The system created was evaluated through the *Experiment 1* carried out at the UH Robot House. The ARS was neccessary to interact with future participants of HRI experiment, collect data and create a module able to recognise users' activities at the UH Robot House. This system was used during all experiments and the data collected were also used by other researchers to further investigate the topic. Further information about how to setup the system and an example rule to detect users activities was described in this chapter.

- **Chapter 4 -** This chapter describes the initial definition of personas integrated into the system, and the process followed to define them. In addition, the system architecture that holds all the modules implemented during this research is described, including the personal behavioural model to adapt the robot's features to users' characteristics and needs. The content of this chapter is supported by the published article (Duque et al. 2013b). The initial questionnaire used to gather the user's information at the beginning of the *Experiment 2* and *Experiment 3* is specified in Appendix C. An iterative methodology was followed during the investigation to incrementally reach the research goal. In addition, the evaluation process to investigate the aimed computational behaviour model is described at the end. This chapter is an introduction to the chapters containing the main experiments of this research, *Experiment 2* and *Experiment 3*.

- **Chapter 5 -** This chapter presents the *Experiment 2* performed at the UH Robot House which investigates the concept of personas in the HRI field. In order to understand how the personas technique could be integrated into a computational behaviour model for robot companions, users' preferences when interacting with a robot companion at home need to be found out. Therefore, the first mission is to evaluate the different robot feature levels that the robot could display during a set of tasks performed at the Robot House. Each of the behaviours is associated with one of the personas defined, so the users preferred behaviours and the variables that represent this association can be later evaluated. The definition, evaluation and outcomes of this experiment are also exposed in this chapter. The conclusion describes what the knowledge acquired and how the results can help to modify the system for the *Experiment 3* of this personas investigation.

- **Chapter 6 -** In this chapter is presented the *Experiment 3* carried out at the UH Robot House. A complete scenario composed of several tasks where the participants are asked to interact and collaborate with the robot companion. The main objective is to evaluate the set of personas defined in the system and the behaviours associated with the robot during the execution of the tasks. Each individual performed the same set of scenarios in a random order during the assessment process. The definition, evaluation and analysis of data for this experiment are covered in this chapter. A final discussion indicates to what degree our expectations have been fulfilled before moving to the final chapter of this research.

- **Chapter 7 -** This last chapter summarises the main findings of this investigation and discusses the significance of the results. In addition, the targeted personas-based computational behavioural model is presented based on the research findings. Furthermore, the list of contributions and the limitations of the current approach are also supplied. Finally, guidelines to investigate the personas technique in the HRI field during future stages are provided following the outcomes of this investigation.

Chapter 2

Related Work

2.1 Human-Robot Interaction

Human-Robot Interaction (HRI) is a multidisciplinary field focused on studying robotic systems that interact directly or indirectly with humans. This field emerged during the mid 1990s and the early years of 2000, although robot behaviour and its consequences for humans have been studied for decades in several fields (Asimov 1986). The good understanding, evaluation and design of these robotic systems would facilitate the creation of more social and human-like interactions between humans and robots. A survey about HRI was presented by Goodrich et al. as a tutorial for people outside the field to get a better understanding of this (Goodrich & Schultz 2007). According to the author, HRI can be divided into two categories: remote interaction and proximate interaction. The main difference between these two categories is the fact that the human and the robot are or not co-located in the same area during the interaction. Within these categories, it is possible to define others subcategories depending on the application, for instance, mobility, manipulation or social interaction. This latter subcategory has been especially popular in-between researchers across the HRI field.

Fong et al. reviewed the field a few years earlier than Goodrich et al. but focusing on social interactive robots, an HRI area where the human social characteristics exhibited by robots during the interaction play a key role in robot acceptance (Fong et al. 2003a). Fong et al. described socially interactive robots as the group of robots where social interaction is the fundamental aspect to consider, i.e. those should show a certain degree of adaptability to be able to interact with a variety of humans. As an example of this, the success of robot companions, created to co-habit with users in their homes, depends on their ability to respond and interact with people in a natural way and not just to help in domestic tasks (Breazeal 2004). Dautenhahn also pointed out the need of creating robots able to interact and cooperate with humans, or even other robots (Dautenhahn 2007). The research presented across these lines is framed inside this area, social interaction, where the robot social skills must be introduced during the interaction in order to improve the robot social perception and acceptance (Ray et al. 2008).

Robot companions must comply with certain social rules in order to adapt themselves to the environment and behave accordingly to theirs users' characteristics. Several definitions of social robots can be found in the literature, but the one proposed by Bartneck & Forlizzi seems the most relevant to our research purposes (Bartneck & Forlizzi 2004) as pointed out in Chapter 1. The authors define a social robot as "*an autonomous or semi-autonomous robot that interacts and communicates with humans by following the behavioral norms expected by the people with whom the robot is intended to interact*" (Bartneck 2004, p. 592). This means that users' expectations and the degree to which robots are able to fulfil those is a fundamental aspect to address in the HRI area, in particular during long-term interactions. In addition to this definition, others must be considered as the one presented by Breazeal, who defines a sociable robot as a "creature" who pro-actively engage with humans in order to benefit humans and also benefit itself, e.g. improving its performance or learning from the environment (Breazeal 2003). This research main target is aligned with the previous lines, the investigation and definition of different approaches that help to incorporate the necessary social skills (Dautenhahn 2007) into robot companions so that the interaction with humans can be enhanced during the first encounter.

In general, the main objective of the HRI field can be defined as the understanding of humans interacting with robots throughout the wide range of environments where both will co-habit in the near future (Breazeal 2004) (Cortellessa et al. 2008). Inside this field, our research group is particularly focused on the social aspect of assistive and interactive robots in smart homes where these social features will play an important role in robot acceptance by humans. Therefore, the incorporation of social mechanisms into robots' behaviour during the interaction must always be considered as robots will be expected to behave as humans would in similar circumstances. This is particularly important in the area of social robotics, where robots will be part of people's lives across several environments, e.g. domestic environment, although different environments can be considered when referring to social robotics (Sabanovic et al. 2007). One way of improving the overall performance of a robot companion when interacting with a human is to endow this with the capability of knowing about the environment and changes surrounding the interaction (Duque et al. 2013a). This will create the possibility of making robots aware of the user's actions and the activities performed during a period of time, so robots could adapt their behaviour to the new context. In the HRI field, it is possible to find efforts to standardise the design of HRI studies and endow robot with social skills during the interaction. Kahn et al. presented a set of design patterns to achieve a high level of sociability during the human and the robot interaction (Kahn et al. 2008). In a more recent investigation, de Graaf et al. presented some guidelines that should be considered when designing social robots in a domestic environment. These guidelines were created from a user's perspective after a longitudinal home study (De Graaf et al. 2015). Therefore, several are the studies in the social robotics area that investigate ways of enhancing the interaction and incorporating social capabilities into robots.

2.2 Human-Robot Interaction Current Challenges

The field of HRI faces great challenges, robots require the ability to adapt themselves to the user's behaviours and needs in order to be accepted into the environment where they interact with humans. Social robots are tools developed to collaborate with people, therefore it is not enough to just develop a robot aesthetically accepted by users (Mori 1970) (Mori et al. 2012); researchers are expected to develop socially intelligent and adaptive agents. One of the main challenges still remaining in the area of social robotics, and the HRI field in general, is the ability to replicate humans' flexibility and adaptability to the environment into robots' behaviours (Fong et al. 2003a). In HRI studies, researchers endow robots with social skills in order to improve and engage their interaction with users (Dautenhahn 2007). The incorporation of these social skills should be addressed during early stages of the development process in order to be displayed from the first interaction.

However, the development of social assistive and interactive robots is not just based on aesthetics, robots need to be developed as a tool to collaborate with people while presenting certain degrees of social features which make them being embraced by users (Mori 1970) (Mori et al. 2012). Therefore, researchers in the field are requested to develop socially intelligent and adaptive robots able to be integrated and recognised in human environments. This desire of bringing autonomous robots into people's lives has greater challenges than traditional robotic applications. Breazeal et al. pointed out that robots should be endowed with features of social and emotional intelligence in order for them to be successfully introduced in our environments (Breazeal 2004). Therefore, the efforts must be concentrated on creating mechanisms to help the field pursue the objective of incorporating social features into robots, especially in domestics environments where long-term interaction are expected between a robot and a human. Creating a robot that cares is a recent investigation presented by Matari, the author exposed the importance of social interaction inside the assistive robotics area (Matarić 2014). The use of gestures, affects, speech or movements will make robots capable of improving human tasks and motivate them during certain activities. However, this is still a challenge and there are too many aspects to be improved and developed in this area in years to come.

Empathy, the capacity to understand the feeling that other person is experiencing, is an emergent research inside the social robotics area as emotional intelligence is attempted to be integrated into robots. Lim et Okuno present a recent investigation where an empathy model was incorporated into robots to recognise adult emotional voices (Lim & Okuno 2015). The authors achieved quite a high success rate detecting happy and sad voices from adults, however this is still early days, and the system has many limitations and challenges to face, for instance, facial expression was not addressed, one of the main components of humans emotions. Leite et al. investigated how robot behaviours could be improved to sustain long-term interactions with users (Leite et al. 2014). The authors presented a empathic model for social robots playing chess able to interact with children for long period of time. The investigation results supported their initial hypothesis: empathy helps achieve a higher rate of social presence and engagement during the interaction. However, the limitations of this study should be taken into account as the investigation was performed in a quite defined scenario. As observed, it is difficult to create general social skills to be incorporated into robots when interacting with users. There are efforts to try to develop standard ways of achieving this, e.g. the tutorial about social and affective robotics presented by Pantic et al (Pantic et al. 2016), however there are too many challenges to be addressed before this can be fully achieved.

As the world enters the new era of technology where robots are believed to be part of our daily lives, the expectations in the HRI field are increasing. The creation of a general-purpose robot is still a challenge that will take years until it can be proven (Sheridan 2016). Regarding domestic environments, personal assistive robots could be expected to incrementally learn users' preferences in order to appropriately adjust their behaviours to different situations. Moreover, humans could also be expected to learn how to interact with robots, so the interaction and adaptation process does not occur in just one direction. All adaptations to be implemented into robot behaviours have to be preceded by a learning process over user behaviours, preferences and needs when interacting with a robot companion. The ability to model this adaptation, so the behaviours shown by the companion are closer to what humans could expect from the system, will improve the interaction and the understanding of user preferences. The correct recognition of users' behaviours and their expectations will elevate the acceptance degree of social robots in domestics environments.

Nevertheless, the creation of these skills cannot always be achieved without running long-term studies to collect user data in order to fully understand users' preferences when interacting with robot companions, e.g. (Butler & Agah 2001) (Koay et al. 2007) (Koay et al. 2009) (Dautenhahn et al. 2006). Machine learning approaches could be used to make robots modify their behaviour as the user interact with the system (Park et al. 2008). Nevertheless, this does not solve the initial problem pointed out at the introduction of this dissertation, the recruitment of participants and the collection of large datasets during HRI studies still remains an arduous task for participants. New approaches should be investigated in the field, so the community will be able to assess and evaluate different approach in the HRI area. I believe that the use of the personas technique (Cooper 1999), widely investigated in the HCI field, and its integration as part of a computational behaviour model for robot companions would contribute to the design and development of HRI systems. This novel approach helps to incorporate the initial social skills and robot behaviours expected by humans into a robot companion. At the same time, it contributes to reduce the amount of training data required to evaluate each individual robot features before adapting this to the user's needs.

2.3 Robot Companions and Smart Environments

Nowadays, it is possible to observe the trend with the IoT (Internet of Things) and how systems get interconnected. In the field of HRI, current researchers focused on smart environments can take advantage of this trend by increasing the number of devices installed in the environment and increasing the amount of data available to investigate. Thinking about the future, one of the common devices to be found at home could be an assistive/interactive robot companion. It should be able to assist humans and make their lives more comfortable, so elderly or impaired people could take advantage of this technology. Moreover, new skills to be incorporated into the robot could be expected as technology evolves which will make robots suitable for a wider sort of users in domestics environments.

In recent years, several European and National projects were released regarding smart homes and robot companions. For instance, *RoboCare*, a multi-agent system designed to generate services for human assistance. It was implemented on a distributed platform and it was meant to be used in health-care institutions or domestic environments (*RoboCare* 2002-2007) (Cesta et al. 2007). The *K-SERA* project aimed to integrate both social robotic and smart homes technology. The research tried to create a successful, effective interaction between humans and robots in order to improve acceptance of service robots in an attempt to utilise this technology alongside with ubiquitous monitoring systems (*KSERA* 2010-2013). *Florence* is a multi-purpose mobile robot platform for assisted living whose target was to improve home care for elderly people. The main idea was to create a robot mobile platform to increase the users' acceptance; as well as being cost-effective for others, for instance, caregivers (Lowet & van Heesch 2012). Similarly, projects like *CompanionAble* and *Mobiserv* combined robot companions and smart homes. *CompanionAble* is focussed on serving persons with mild cognitive impairments and supplying company to support their well-being at home (Badii et al. 2009). The second project mentioned, *Mobiserv*, was created to support elderly people with dementia and physical disabilities with their activities of daily life while providing health-care and wellness monitoring, e.g. (*Mobiserv* 2009-2013) (Heuvel et al. 2012) (Caleb-Solly et al. 2013).

Our research group was involved in the last decade in three different European projects. COGNIRON whose overall target was to study different cognitive capabilities of a robot in a human environment (*COGNIRON: The Cognitive Robot Companion* 2004-2007). The robot was able to grow its capacities to interact and assist humans during their daily activities as the project progressed, at the time that new technologies were applied to the system. LIREC was focused on creating intelligent companions capable of establishing long-term interactions with humans (*LIREC: Living with Robots and Interactive Companions* 2007-2013). The interdisciplinary team was investigating both virtual and physical companions and how people reacted when migrating the companion from an embodied physical representation to a virtual one. The latest project was ACCOMPANY, a mobile service robot platform based on Care-O-Bot (Graf et al. 2009). The service robot was focussed on fetch and carry tasks to support elderly people during their daily tasks at home (*ACCOMPANY: Acceptable robotiCs COMPanions for AgeiNg Years* 2011-2014). The UH Robot House was the environment used to integrate the research done across several European partners.

Other recent examples of researchers investigating robot companions and smart homes can be found in (Huijnen et al. 2011) (Badii et al. 2012) (Syrdal et al. 2013). In this context, it seems sensible to investigate new techniques to cope with the current HRI challenges already identified. Integrating the personas technique into the field as part of a computation behaviour model would allow us to identify the type of users interacting with the system, so the robot behaviours can be adapted accordingly. The investigation of robot companions and smart homes environments provides a clear advantage from a research point of view. A controlled environment like those supply the opportunity of carrying out studies and analysing users' behaviours under the same conditions while exposing users to a realistic and natural environment.

This advantage allows the researcher to focus on possible problems found during the evaluation process. This helps to increase the knowledge of the system and improve its adaptation to the user's needs during the interaction. This advantage should be used to effectively tackle issues in the HRI field and learn in a quicker way about the future problems to overcome.

2.4 From Human-Computer Interaction to Human-Robot Interaction

The field of HCI is focused on providing the mechanisms to allow users to enhance their experience when interacting with a computer or similar device. Its main goal is to understand the way the users interact and feel when using the system. This field has greatly evolved from early stages of just exploring direct interaction with computers towards the appreciation of other variables like usability, usefulness or social impact (Kiesler & Hinds 2004). The technological advances in the last decade have increased the presence of HCI techniques into the field of HRI. The processes of design and usability applied to computer systems have developed a large significance when developing a social interactive robotic system in HRI.

Both the HCI and HRI fields were always closely related as they focus on the interaction of humans with computer technologies. As early studies in the field of HCI revealed, users develop relationships with computers even when they are aware of the computer being an artificial entity (Reeves & Nass 1996) (Nass et al. 1994). Therefore, it could be expected that HRI users develop social behaviours towards the robots as they interact with them. This association between the two fields is a valuable reason to consider that a technique widely investigated in the HCI field should bring similar results into the HRI field. The investigation of a HCI method into HRI is not a novel approach, some researchers are focused on user-centred design for robots, e.g. (Fernaeus et al. 2009), which gives an indication that the community is interested in investigating how HCI techniques can contribute to different areas of the HRI field. However, the use of these techniques cannot be directly applied to the HRI field due to the varying forms that a robot could be presented and the cultural differences that could be found (Bartneck et al. 2005), which tends to be different from computers or tablet devices.

Advances in technology are leading towards a robotic revolution which will offer a greater degree of involvement of the HCI community. Therefore, researchers should take advantage of the features in which both fields converge, making use of the tools used in the HCI field to obtain similar benefits when applied to the HRI field. I believe that the utilisation of well-known HCI tools for the design and the development of a social interactive system will help to create more socially adaptive robots to interact with humans. Breazeal et al. pointed out that HCI-like studies could be applied to HRI studies in order to get a more advanced understanding of how people interact with robotic technology (Breazeal 2004). This is especially important in environments like a smart home where both the human and the robot will co-habit in the same space for long periods of time. However, despite the relation between the two fields, the limitation of using techniques in a different field must be considered. According to Scholtz et al. there are six dimensions in which both the HCI and the HRI fields differ from each other (Scholtz et al. 2004):

- Different requirements based on interaction roles.
- Interaction of the platform in the physical world.

- Dynamic nature of the hardware.
- Environment in which the interactions occur.
- Number of platforms that the user is interacting with.
- Autonomous behaviour of the platform.

These dimensions indicate the difficulties that could be faced during this investigation. The use of HCI techniques in robot companions compared to more traditional hardware platforms could not be trivial and people's reactions to robots could differ from the initial expectations. In addition, the difficulties in prototyping and running HRI studies need to be taken into consideration when investigating and integrating HCI methodologies into the HRI field. Fong et al. pointed out that HRI differs from HCI because of the dynamic and changing real-world environment that the field is concerned with (Fong et al. 2003b). In HRI the interaction may happen through a user interface or proximal interaction, which include an extra level of complexity when compared to HCI. Taking into consideration common and different features between the two fields, a new approach to introduce the personas technique into a computational behaviour model for robot companions in the HRI field has been investigated. This approach will allow the design and the development of HRI systems where the companion behaviours are adapted to user's preferences at the first encounter. To the best of my knowledge, this approach has not been investigated yet, which could indicate the difficulties on modelling users in a complex environment such as smart homes. However, this investigation should bring interesting results to be used in future research on the field.

2.5 The Personas Technique and Scenarios

During the design process of a new product, the collection of data from targeted user and their goals using the future product is a primary goal. The User-Centered design (UCD) approach was created as an attempt to focus the design activities upon users' characteristics instead of just the external design of the system (Bailetti & Litva 1995). This approach allowed designers to concentrate their efforts on understanding the user's needs and goals during the development stages of the system. However, many designs still lack the usability and features expected by users. One of the problems found when using the UCD methodology was to effectively communicate the requirements to the designers. Often the described users were not seen as real persons, so their needs were abstract and undefined to designers (Pruitt & Grudin 2006).

In this context, Alan Cooper presented an alternative to this UCD philosophy used in the field of HCI during several years. This alternative was defined Goal-Directed Design (Cooper 1999). The new approach was based on the understanding of the user's needs and goals, and the definition of guidelines to adapt a system to the final user. At the same time, a new concept was introduced by the author, personas, to represent users archetypes of a system. According to Cooper, "*personas are not real people, but they represent them throughout the design process. They are hypothetical archetypes of actual users. Although they are imaginary, they are defined with significant rigour and precision*" (Cooper 1999, p. 124). Personas are considered a key component during the design process, where it helps designers and developers create a mental model of future users of the system and extract their goals and needs for the product to be developed. Numerous studies demonstrated the usability and benefits of the personas technique along the design process, e.g. (Chen et al. 2011) (Chen et al. 2009) (Long 2009) (Nivala et al. 2011) (Pruitt & Grudin 2003). Other researchers, e.g. Castro et al., modified the initial definition of the personas technique to the so-called "personas*" (Castro et al. 2008). The author extended the set of steps defined by Cooper (Cooper et al. 2007) to create personas and enriched the requirements analysis to allow designers to focus on the users of the future system. This shows how the technique is still being used and evolved to match the latest requirements of current systems designed in the field of HCI.

In general, the definition of personas must be described through a detailed narrative to address as many details as possible about their lives and activities, as well as describing the goals, needs and frustrations of using a particular system or product. Note, the more specific the definition of a persona is, the more useful this is as a design tool. The only fictitious data to be created are the name, the picture or the personal details. The character represents a group of users, but even so, it should be represented as a single person and seen as a real person. This helps the designers to focus on this person and stop speaking about general user requirements that could lead to the natural tendency of being affected by our own preferences and needs (Pruitt & Grudin 2006). A good definition of personas should generate empathy which benefits designers to more effectively address the user's needs and goals using the product or system. According to the usability expert Donald Norman, empathy in the personas context means understanding how the population use a product in a ready and easy manner without frustration (Norman 2002). In order to have some guidelines about how to create personas, the steps followed by a well-known researcher in the field were adopted. Lene Nielsen is focused on the personas technique and scenarios for several years, e.g. (Nielsen 2002) (Nielsen 2003) (Nielsen 2004) (Nielsen 2012). According to Nielsen, personas should be defined upon five characteristics to avoid falling into stereotypes as described in (Nielsen 2008):

- Body: a photo or a description of how the person looks creates a feeling of the person as a human being; posture and clothing tell a lot about the person.
- Psyche: overall attitude towards life and our surroundings which also influence the way we meet technology e.g. the persona is introvert or extrovert.
- Background: we all have a social background, education, upbringing which influence our abilities, attitudes and understanding of the world.
- Emotions and attitudes towards technology and the domain designed for.
- Personal traits: According to Nielsen, there are two types of characters, flat and rounded. The flat characters are characterised by having only one character trait which is reflected in their actions and creates a highly predictable character close to the stereotype. The rounded characters have more than one character trait, is not predictable and creates engagement.

These characteristics will guide the definition of the initial set of personas to be created in our system. Each persona will be represented by a picture, a description of his life, the background and education, the attitudes towards robot companions and how the character is expected to use and interact with the robot during activities of daily living. These personas will be based on previous data collected by our research group (Dautenhahn et al. 2005) (*COGNIRON: The Cognitive Robot Companion* 2004-2007), including the knowledge from the *Experiment 1* carried out during our research (Duque et al. 2013a). One of the main challenges to be faced during this investigation is the definition of the significant variables that our computational behaviour model should incorporate. These variables must represent the set of user characteristics to consider when matching a user to a persona. During the interaction, the robot features will be modified to match the behaviour associated with the peronas that best represent the type of user interacting with the system. These robot features will be defined after considering the robot hardware and the environment limitations where the interaction will take place as they will be presented in Chapter 4.

Alongside to the creation of personas, the definition of scenarios will help to narrow the set of robot behaviours to be presented during the interaction between the user and the robot companion. Cooper defined these scenarios as "*a concise description of a persona using a software based product to achieve a goal*" (Cooper 1999, p. 180). Carroll defined the scenarios as stories in which people and their activities take place (Carroll 2000) . The scenario definition is based on goals, actions and the interaction of the user with the system. They are used to represent the user's objectives and how these are achieved using the resources in the environment. Scenarios are used not only as a tool to represent the user's goals but as a method to design and develop robots behaviours during the interaction with users, i.e. how the robot should react in a particular situation and based on the contextual information. In addition, scenarios could be used as a guideline to evaluate the system after performing HRI experiments. This scenario-based methodology has been supported by other researchers in the field of HRI during the last few years, e.g. (Robins et al. 2008), (Carroll 1995) (Rizzo et al. 2003) (Benyon & Mival 2008) (Compagna et al. 2009) (Nani et al. 2010). In the course of this dissertation, the research findings will be presented after evaluating the first set of personas and the initial model to be defined against participants in the UH Robot House. The definition of scenarios will help to describe the way in which robot behaviours must be modified to suit the user's expectations and needs during the interaction in the smart home.

2.6 The Personas Technique in Human-Robot Interaction

In the literature, a few studies using the personas technique can be found in the HRI field, however, their aim seems different to the one presented by this research. For instance, Ljungblad et al. used personas to describe people with interest towards animals, comparing human-animal interaction with human-robot interaction (Ljungblad et al. 2006). In a similar study (Ljungblad & Holmquist 2007), the authors used scenarios together with the personas methodology to design a set of technological prototypes that consider the user's interests. Other related works are mainly based on the scenario-centred design technique, in which personas are considered the main component of the design process, e.g. (Robins et al. 2008), (Carroll 1995) (Rizzo et al. 2003). Another example is presented by Benyon et al., who used the combination of personas and scenarios to define the requirements to build companion technologies that could be adapted to users' needs (Benyon & Mival 2008). Similarly, Compagna et al. suggested to use a scenario-centred design in order to improve the development of mobile robot assistants used in care facilities (Compagna et al. 2009). Huijnen et al. introduced the idea of robot personas in their studies (Huijnen et al. 2011). The authors found that the perceived trustability and responsiveness of the robot based on its persona and role seem more important than the physical robot embodiment to achieve the user's satisfaction during the interaction. In their latest work, Ruckert et al. suggested to explore and implement multiple personas inside a robot so that the robot's personality could be changed depending on the specific context (Ruckert et al. 2013). Recently, Dos Santos et al. focused on a methodology approach to define personas that considers human behaviours and psychological aspects as fundamental characteristics to develop new robot applications and create social robots focused on users (Dos Santos et al. 2014).

Therefore, the use of personas inside the HRI field has been presented as a guiding concept to design a product, e.g. a robot companion, and in some cases, to design different personalities in robots during the interaction. However, to the best of my knowledge, none of the investigations mentioned was investigating the connection between user characteristics and personas in order to define a computational behaviour model for robot companions in the field of HRI. In this novel approach, personas are used to match users to the pre-defined personas of the system so the robot's behaviour can be adapted to the identified user and needs in a domestic environment during the first encounter. Thus, personas are not pure conceptual descriptions but are a key component of the computational behaviour model targeted and the system architecture to be explored alongside this research. This model considers several variables in addition to the user's personality, so its complexity gets increased compared to similar models, e.g. (Tapus & Matarić 2008) (Aly & Tapus 2016). On the other hand, a larger number of variables gives the possibility of evaluating and further adapting the initial model based on the iterative methodology followed during the investigation. Finding the match between personas and the user interacting with the system and, then modifying the robot's behaviour to adapt the system to this particular user can be defined as the main target to investigate during this novel approach.

Recently, a conceptual model of personas has been defined for HCI applications (Negru & Buraga 2012a) (Negru & Buraga 2012b). The authors defined an ontology to represent concepts and properties of the personas methodology used in the HCI field. However, that approach differs from the new approach defined for this investigation, where personas are a key component of a computational behaviour model for robot companion in a domestic environment. This novel approach tries to cope with the problems pointed out in HRI studies, where the user data collection and the recruitment of participants still take large efforts before the HRI system is able to incorporate social skills into robot companions to enhance the first encounter with humans. The outcomes of this research will show the direction to follow in future investigations of the personas technique inside the field and the development of socially interactive robot companions for home environments.

2.7 Behaviour Models in Human-Robot Interaction

During this research, the benefits of using personas in the field of HRI and integrating this into a computational behaviour model for robot companions will be investigated. In the literature, it is possible to find several behaviour models definitions applied to intelligent agents, either robots or virtual agents. The majority of efforts are focused on developing models capable of achieving believability and empathy in agents and robots in order to engage users during the interaction in a variety of environments. Several are the factors that can be considered during the definition of a model. In this investigation, a large number of factors will be initially introduced in the model and the iterative methodology will help to reduce and focus on those more relevant to successfully achieve the research target. The most influential models in the field are presented in order to get a general knowledge about the current state-of-the-art.

The discussion has been separated into two main sections, agents and robots model. The knowledge from both area has been important to investigate the personas-based computational behaviour model described in this dissertation.

2.7.1 Agents Model

Appraisal theories state that emotions result from people's interpretations and explanations of their circumstances (Aronson et al. 2005). Computational models of emotions are useful in a variety of domains, but particularly important in games, virtual reality and the HCI field. These models are inspired in appraisal theories which try to understand why certain emotion's responses are exhibited when facing an event and the variance found among different individuals. Therefore, developing a model able to cope with all different circumstances that the system will be exposed to during the interaction with humans will be a quite challenging task. Broekens et al. attempted the creation of a scalable emotions model for agent in games starting from simple models (Broekens & DeGroot 2004). They proposed a new framework to cope with the diversity and adaptability that previous model are not prepared for in the gaming field. Their results looked promising in terms of modularity and the capacity of the model to be expanded. These two factors, adaptability and flexibility, must be considered when developing a computational behaviour model.

A year later, Dias et al. built the *Fatima Behaviour Model* in which the agent's reasoning and behaviour are influenced by their emotional state (Dias & Paiva 2005). The behaviour model is defined through a set of goals, a set of emotional reaction rules, action tendencies and emotional threshold and decay based on "the OCC model" of emotions (Ortony et al. 1988). This model was adapted and integrated into a robotic system as part of the LIREC project (*LIREC: Living with Robots* *and Interactive Companions* 2007-2013). The project integrated this model into a three-layers architecture to adapt the robot's behaviour on the basis of the user's emotional parameters defined in the system. This model helped as inspiration for the definition of the architecture and system currently present in the UH Robot House (see section 4.4). However, emotions and personality were the main components of the model presented by Dias et al. In order to achieve a smooth interaction between a robot and an user at home some other factors must be considered and integrated into the model. For example, proactiveness, proxemics or assistance level in order to transform the companion in a useful tool for the human. This was the main reason to develop a new model, although considering the Fatima model's architecture and outcomes to define the computation behaviour model presented in this dissertation.

2.7.2 Robots Model

When discussing about behaviour models for robot companions a large number of factors must be considered. This makes difficult the task of creating an empathy robot to interact with users in a variety of environments. Smarts homes are a particularly challenging environment as both, the robot and the human, are expected to co-habit for several hours, days or months in the near future. Improvements in this area will positively contribute to the development of the HRI field. Understanding the challenges to be faced will help achieve an appropriate interaction level for humans and robots in a home environment.

In (Tapus & Matarić 2006) (Tapus & Matarić 2008), the authors describe a behaviour model for assistive robots that modify their social interaction parameters according to the personality, introversion and extroversion, of post-stroke patients. Proxemics, speed and vocal content the robot characteristics modified in order to help patients improve their performance during certain tasks. This model was created for a specific group of participants and trained to improve the interaction between the user and the robot in a quite delimited environment. The model investigated during this research includes a wider variety of users and robot features to be considered from the initial stages of the development process.

Satake et al. created a robot behaviour model to proactively initiate a conversation in a shopping mall (Satake et al. 2009). Based on a learning process, the author explored how the approach distance between human and robot could be improved to establish a smoother conversation with a selected user. It seems quite interesting how the authors found the robot proactinessa useful mechanism to catch people attention and initiate the conversation. This model was develop for a quite specific environment, so the knowledge and the outcomes exposed will be really useful but its limitation must be considered when developing the computational behaviour model proposed during this research. Nevertheless, the model presented represented the right direction to define behaviour models capable of interacting with people in an effective way. The data collection will still be necessary to develop and modify the model proposed by Satake et al., this is why the pesonas-based model may propose a really useful methodology inside the HRI field.

Another model example, although not related to the smart homes or the robot companions research, was mentioned during the previous sections. A recent conceptual model based on personas has been developed in the field of HCI (Negru & Buraga 2012a) (Negru & Buraga 2012b). It defines an ontology to include concepts and properties used for the definition of personas. The author tries to identify the sorts of users that will interact with the system based on the characteristics defined into the model. This is similar to the initial methodology that will be presented in this dissertation, but it does not considered robots or the environment where the user will interact which makes our research relevant into the HRI field. The importance of the environment and the context awareness was already pointed by Negru et al. in the conclusion of her investigation, something it is already considered for the definition of the computational behaviour model thanks to the ARS system described in Chapter 3. More recently, Xu et al. investigated a behaviour model for HRI to express mood using the body language (Xu et al. 2015). Different gestured were coded into a robot to display a positive or negative mood to participants. The parameterized behaviour model revealed the importance of the robot expressiveness to improve user tasks performance during the interaction. In addition, the study demonstrated the mood contagion effect between participants and robots, making the expressiveness a key component to be incorporated into robots in order to show social skills.

Additionally, and indirectly related, Casas et al. presented an intelligent monitoring system to help elderly people overcoming their difficulties (Casas et al. 2008). The main purpose was to create a safe and intuitive environment where the household could independently perform home tasks for longer. The concept of persona was used to define users' profiles in order to determine the features that the system should adopt to suit the user preferences when interacting with the system. The successful approach presented demonstrates once again, the benefit of using personas and the importance of following a user-centred approach when developing systems for a defined group of people.

The proven success of the personas technique in HCI studies could be used to tackle the current problem of recruiting participants in order to adapt an HRI system to the user's needs. The creation of a model to automatically adapt the system based on the match between the user and the pre-defined personas of the model could represent a real benefit for the HRI field once the model is achieved. The use of personas helps to define the robot social skills expected by users when first interacting with a robot companion, meaning that the creation of such a model will reduce the burden put on participants in early stages of the system development. Classic system development strategies, specially in the field of HRI, needs extensive user data to be collected in order to adapt the robot behaviour to participants during the interaction. During the investigation of the computational behaviour model based on personas, a wide number of variables will be initially considered. However, this number will be reduced after performing the *Experiment 2* and *Experiment 3* where the connections between personas, users and their preferences will be evaluated when interacting with a robot companion at home. As it could be expected, a larger number of variables to study will increase the complexity of our system, however, it should provide a better knowledge and understanding of the challenges to be faced during this investigation and the definition of the personas-based model.

2.8 Variables to Be Considered in Human-Robot Interaction

In the field of HRI is possible to find several frameworks investigating different robot features regarding robot companions and smart homes. Those will be used during our research to guide the definition of the variables that must be considered for the initial personas-based behavioural model. As mentioned in the introduction chapter (see Chapter 1.4), an iterative methodology will be followed to evaluate this investigation. A large number of variables will be introduced in the initial definition of the model in order to cover a wide number of users and robot behaviours combinations. The use of variables already investigated inside the HRI field allows focusing on the main research question instead of individually evaluating the feasibility of each individual variable inside HRI studies. This is the main reason to present some of the main frameworks and investigations already evaluated in the field and use them as a guide to define the initial approach of the model. From personality to proxemics, all variables seems to play a different role during the interaction, therefore, it will be quite important to evaluate how they could affect users during the interaction with the companion.

2.8.1 User Personality

As Zimbardo stated, personality is "the psychological qualities that bring continuity to an individual's behaviour in different situations and at different times" (Zimbardo et al. 2012). Personality affects the manner in which people behave with a robot, so it definitely needs to be taken into account during the interaction. In some of the HRI studies mentioned above, the user's personality was considered one of the most influential factors during human-robot interaction. Following these lines, some of the personality theory models are presented below. They are currently used in the HRI field to evaluate the user's personality.

Eysenck's Three-Factor model (PEN) of personality (Eysenck 1991) and the Five-factor model of personality, also called *Big-Five* (Digman 1990), are widely used models in the HRI literature. The Eysenck's model describes personality through the following factors: (P) *Psychoticism*, (E) *Extroversion* and (N) *Neuroticism*. The especial treatment of the Extroversion and the Introversion traits makes this model suitable for this research purpose. Nevertheless, little research can be found in the other two factors and their impact in HRI studies with robot companions. In addition, the second personality model presented will supply a larger number of dimensions per user to be studied, so it was decided not to consider the Eysenck model for this research. Instead, the Five-factor model has been shown as an emergent and valid personality model for HRI studies (Digman 1990). As an example, the model has been successfully used in several research projects in our research group (*COGNIRON: The Cognitive Robot Companion* 2004-2007) (*LIREC: Living with Robots and Interactive Companions* 2007-2013). The following traits are described in this model: *Extroversion*, *Agreeableness*, *Conscientiousness*, *Emotional Stability* and *Openness*. It considers extroversion and introversion, in addition to other traits which have not been found as significant as the previous two traits, but they may still help to define the user's personality for the targeted model. Therefore, the Five-factor model supplies the diversity that this system should integrate in terms of personality traits. This will make possible to study a variety of user's personality traits that could be found as influential during the evaluation of the behaviour model.

According to Gosling et at. the Big-Five model could be defined as "a hierarchical model of personality traits with five broad factors, which represent personality at the broadest level of abstraction" (Gosling et al. 2003). The author created a test form for this personality model, called TIPI (Ten-Item Personality Inventory) (*TIPI - Ten Item Personality Measure* n.d.). It is composed of 10-items that are ranked between one to seven using the Likert scale supplied in the form, see Appendix C.2. The score for each trait will be re-coded and calculated as specified by the author to obtain the final value for each of the five traits considered in the personality model. The TIPI has been widely adopted due to its facility to be completed and process the data during the analysis stages. Therefore, this form will be integrated into the studies, see Table 1.1, in order to evaluate the user's personality.

2.8.2 Human-Robot Proxemics

Proxemics was a term introduced by Hall decades ago (Hall 1966). It was defined to measure the interpersonal space created between humans during a social interaction. Nowadays, this term is widely used in HRI studies under the assumption that humans interact with robots in the same way that they interact with other humans (Fong et al. 2003a). Hall provided a framework in which the main spatial zones during interaction are categorised. However, the visual method used by Hall lacked the precision given by Lambert in his later study (Lambert 2004). In this last one, Lambert defined the interpersonal human-human space currently adopted by HRI studies (see Table 2.1).

Range	**Situation**	**Personal Space Zone**
0 to 0.15m	Lover or Close Friend Touching	Intimate Zone
0.15m to 0.45m	Lover or Close Friend Only	Close Intimate Zone
0.45m to 1.2m	Conversation Between Friends	Personal Zone
1.2m to 3.6m	Conversation to Non-Friends	Social Zone
$>$ 3.6m	Public Speech Making	Public Zone

Table 2.1: Human-Human Personal Space Zones - Lambert (2004)

Using this space, Walters et al. presented a framework to represent proxemics in human-robot interactions, based on studies carried out in a simulated living environment (Walters et al. 2009) . A related study was performed by Mumm et al. to evaluate how people physically and psychologically distance themselves from robots (Mumm & Mutlu 2011). Mumm found that there were differences in the distances kept from the robot by different people, depending on their preferences towards the robot. Similar studies can be found in the literature, e.g (Walters et al. 2005) (Dautenhahn et al. 2006) (Syrdal et al. 2008) (Takayama & Pantofaru 2009) (Koay et al. 2014), where personality traits or attitudes towards robots were identified as influential variables when investigating proxemics in HRI studies. For instance, the *Extroversion* trait is associated with a higher tolerance when being approached by a robot companion (Syrdal et al. 2006). A similar statement was pointed out by Hall, although related to human-human interaction (Hall 1966). Therefore, proxemics must be considered as one of the important factors to include in the model in order to enhance and adapt the interaction between the human and the robot during the first encounter.

2.8.3 Robot Personality and Role

There are two criteria that any robot companion must satisfy when interacting in a domestic environment (Woods et al. 2007): Robots must be able to perform useful tasks for the users of the system, and these tasks should be carried out in a socially acceptable manner during the interaction with the people who share the environment with the robot. Based on these criteria, Wood et al. investigated how personalization of the robot in terms of robot personality could contribute to enhance the user experience during the interaction. Similar experiments were carried out in our research group where different robot roles were presented to investigate participants' perception of future robot companions (Dautenhahn et al. 2005). In addition, the impact of robot personality over the preferred robot approach distance was also evaluated (Syrdal et al. 2006). Heerink et al. performed a study with elderly people where they were exposed to two different robots, one with less social abilities and the other with more social abilities implemented (Heerink et al. 2008) . The results showed how the latter robot, having more social abilities, was perceived as more enjoyable and sociable that the first robot, and this increased the users' intention to use the system.

More recent studies can be found in this direction inside the social robotics area. For instance, Hamacher et al. found that a robot companion incorporating more human-like behaviours will increase its acceptability by users (Hamacher et al. 2016) . The results indicated that a more expressive robot was preferred over the more efficient one during a task performance evaluation scenario. This indicates that a more expressive robot helps to mitigate dissatisfaction when unexpected robot behaviours occur during the interaction with individual participants. Similarly, Aly and Tapus presented a robot platform able to match robot personality with a user personality, introversion and extraversion traits, during the interaction (Aly & Tapus 2016). The results demonstrated the importance of matching robot and user personality in order to enhance the interaction. Lee et al. proved through their study that robots personalisation increased cooperation and engagement during the interaction between a user and a delivery robot (Lee et al. 2012). Huber et al. defined a set of different social roles to be applied to an assistive robot for two specific user groups to achieve long-term acceptance (Huber et al. 2014). The author created these roles based on the results of two studies with users over 70 years old and living either at home or in care facilities. The resulting roles and their concrete robot behaviours should be used as a guideline to design socially assistive robots for the specific user groups investigated.

Hence, the process of adaptation to the final user using the robot personality and roles seems a fundamental task that some researchers in the area of social robotics are already addressing. Exhibiting a distinctive robot personality and character in reaction to the user's characteristics and needs is a needed skill to be added to robot companions during the research process. The integration of the personas technique as a part of a computation behaviour model for robot companions directly contributes to this particular investigation area inside social robotics.

2.8.4 Other Factors to Consider

Robots will become part of people daily lives in the near future. The change from virtual agents to physical agents, i.e. robots, it is an important steps were several factors need to be considered. The design of robots must take into account the association that users will do between the robot body and the environment. The presence of a physical robot will be seen more enjoyable than the interaction with a virtual agent or one separated via video conference (Wainer et al. 2006). The natural dialogue needs to be ensure for any embodied home character by providing feedback through the conversation or the body language. Bartneck et al. investigated the influence of the character's embodiment and its emotional expressiveness during the interaction (Bartneck 2003). The author found the presence of a physical robot helped the user to put more effort into the tasks that he was performing during the experiments. However, Bartneck rejected the null hypothesis and concluded that not necessarily the user experience was more enjoyable with a robotic character than a screen character. This also points out the importance of designing good interfaces to interact with participants.

People attribute human-like qualities and capabilities to robots. It is important to consider the key role play by the mental model that users create a priori based on the robots behaviours. Undoubtedly, the safety must be guaranteed otherwise this mental model can be altered and the observed human-robot interaction could be unexpected. Bartneck et al. performed an experiment to understand the importance of the robotics face expressiveness when attracting participants' attentions (Bartneck et al. 2009). The authors found a strong correlation between a robot's perceived intelligence and the robot's animacy. In addition, the author pointed the importance of defining a quite expressive face in order to attract users' attention more easily. The user's robot perception should be evaluated when exposing participants to a new embodied robot in order to better understand the outcomes from a HRI experiment. A well-know robot companion in our research group will be used for this research in order to facilitate the investigation of the personas-based computational behaviour model aimed.

Robot's aesthetic is considered another influential variable during the interaction with robots. The relationship between robot appearance and human behaviour has been widely investigated in the HRI field. Aesthetic perception of the robot and its social integration seem to be linked. Therefore, it will be important to know the influence that a robot's shape could cause over the user's conduct towards the robot during the interaction (Tondu & Bardou 2009). Exploratory studies of users preferences over robot appearance and behaviours can be found in the literature. For instance, Walters et al. investigated in several studies the effects of robot shapes and behaviours in order to collect people's perception about robots with a different appearance (Walters et al. 2007) (Walters et al. 2008). Video based studies indicated that participants' rating were affected by the consistency between the robot appearance and the robot behaviour. Participants tended to rate behaviours less favourably if the appearance of the robot did not match the expected behaviour. However, Walters et al. concluded that this result depended on the user's personality, the introversion and emotional stability personality traits which were observed to be statistically significant when rating mechanical looking over human-like looking preferences. In addition, Walters et al. highlighted that the appearance of the robot was creating certain expectations about the capabilities of the robot.

In a more recent study, de Graaf et al. found that anthropomorphic robots were rated more positively than alternative shapes robots, e.g. zoomorphic, or functional robots (De Graaf & Ben Allouch 2014). Although, the negative attitudes towards robots were affecting the results. The author concluded that more positive information about domestic robots could contribute to a better overall rating of their design. This finding supports the importance of briefing and presenting the whole system to participants prior to the performance of the experiment to mitigate the effect of users' assumptions over the system. This will be taken into account during this research experiments, and participants will have first a brief introduction to the environment and the robot companion's capabilities in order to avoid participants' expectations and pre-assumptions to bias the outcomes of the study.

It is important to create robot behaviours that suit users in the environment where the interaction will take place. For instance, Sidner et al. investigated engagement gestures to keep the user's attention and maintain a successful interaction (Sidner et al. 2004) (Sidner et al. 2005) . Sinder et at. tested the system in two different modes: robot using engagement gestures and not using engagement gestures. The outcomes from the study indicated how participants preferred the robot using engagement gestures considering the interaction more appropriate that the second mode where the robot did not make use of any gesture. Bruce et al. implemented an attention seeking behaviour to interface with users during the interaction (Bruce et al. 2002). The authors measured the impact of predefined robot behaviours and how they affected the user's desire to initiate the interaction with the robot. The results did not increase the interest shown by participants to interact with the robot. The authors interpreted this unexpected outcome as a consequence of the experimental design, hence the importance of carefully defining robot behaviours adapted to social interactions.

Taking all these variables into consideration, the Sunflower companion, see Section 4.3, seems a good choice to perform the future experiments and carry out this investigation due to its high acceptance level proven across several studies (Koay et al. 2013) (Salem et al. 2015) (Koay et al. 2016). This will allow to be focused on the investigation of the personas model without worrying about the robot embodiment or aesthetic and how this could affect the participants evaluation during the interaction in the UH Robot House. Re-using outcomes from previous research done in the same environment and using the same robot companion open the door to quickly define new investigations in order to move forward inside the HRI field.

2.9 Discussion and Conclusion

As described during this chapter, HRI faces great challenges ahead. Researchers across the field focus their efforts on adapting robot to user's needs and their characteristics in order to improve robots' acceptance. This is especially important for robot companions which will co-habit in the same environment that humans, so they must be successfully integrated into our society and daily tasks. However, they are evident difficulties achieving this adaptation during the interaction. Nowadays, participants are required during early stages of the development and evaluation process of an HRI system. Therefore, a big burden is put on them when running long-term experiments in order to individually personalise the system to their needs when interaction with a robot companion. This is one of the main reasons to investigate a different approach using the personas technique inside the HRI field. The target will be to create a computation behaviour model for robot companions that automatically set the minimum social skills expected by humans during the first encounter without the need of collecting user data in advance. The research questions to be investigated, evaluated and answered during this dissertation are as follows:

1. RQ1: *Which system architecture should we define in order to create a computational system able to automatically adapt a robot companion's behaviour to users based on their needs?*

   In order to introduce the personas technique inside our HRI system, a scalable solution needs to be defined to allow the integration of several modules and the their modification during the iterative methodology followed. At the same time, the system should provide the possibility of being integrated or migrated into a similar environment with ease. The UH Robot House will be the environment to deploy and test this architecture, where the previous system will be adapted to the newly designed architecture.

2. RQ2: *Would people with a similar background, characteristics and personality prefer the same robot behaviours and responses during the interaction?*

   In order to build a computational behaviour model for robot companions based on the personas technique, we need to find out whether participants with similar characteristics have also similar preferences when interacting with companions. During the investigation, user data will be collected in order to answer this question and explain possible difficulties that could be faced when defining the computational behavioural model.

3. RQ3: *Which are the most significant variables found that could help identifying the users' preferences and needs so we are able to adapt the system appropriately?*

   As mentioned during this chapter, several user variables need to be initially considered for the computational behaviour model. The initial selection of these variables will be guided by previous research studies done in the field of HRI and robot companions. As progress is made in the investigation, the most significant variables to include in the model will be defined. Those variables will be used to determine the match between the user and the pre-defined personas in the system. This association will provide the set of robot behaviours that could best suit the user's preferences and needs when first interacting with the robot.

4. RQ4: *Which are the advantages and disadvantages of integrating the concept of personas into the development process of a computational behaviour model for robot companions in smart homes?*

   Some studies already demonstrated the advantages of using the personas technique in the HCI field. This technique was introduced in the field of HRI by other researchers, however, this research defines a novel approach using personas in HRI studies. The personas technique will represent the central module of the computational behaviour model which will make decisions about how to adapt the robot's behaviour to match the user's needs and preferences during the interaction. The investigation to define and create this personas-based model will provide a good insight into the benefits and the difficulties of this approach and the future direction of this research.

5. RQ5: *Which robot features should be adapted based on the research outcomes investigated during this dissertation?*

   During the interaction between a human and a robot several are the robot features that could be modified to enhance this interaction. The goal of defining a general general behaviour model will be used to guide the initial definition of robots feature that should be considered into the model. In general, common features that can be found in robot companions nowadays. The experiment outcomes should help delimit which of the initial set of variables should be discarded or defined as default for all types of users, while other should be modified accordingly during the interaction. At the end of this research, these selected features will be presented and the process by which they were selected.

Chapter 3

Increasing Context Awareness for Robot Companions

3.1 Introduction

The Robot House (Figure 3.1) is a naturalistic environment used by our research group to perform a variety of HRI experiments. This environment offers the necessary resources to test different HRI related approaches in a realistic domestic context which makes users more comfortable and relaxed during a study. Proxemics, habituation effects to robots and other variables were already studied as part of our research group's investigations, e.g. (Walters et al. 2007) (Walters et al. 2008) (Koay et al. 2007) (Koay et al. 2009) (Syrdal et al. 2006) (Syrdal et al. 2008) (Saunders et al. 2016). The results from previous studies in the research department provide valuable information about the social skills expected by users, and how robot companions should adapt their behaviours to individual participant's preferences and needs based on the current context of the system. Context awareness is a fundamental feature that an HRI system should have in order to understand the current status of the system and react according to the user's expectations and requirements during the interaction.

However, the recognition of human activities is not always trivial. Detecting the current activity being performed could require a large amount of user data previously collected on the environment. Otherwise, it could be difficult to recognise the activity pattern and adapt the system to the contextual information processed. Unfortunately, the recruitment of participants for data collection was already pointed out in the literature as one of the current problems in the HRI field. The inclusion of participants during the design and development stages of HRI systems is still an arduous task (Bien et al. 2008) and researchers usually face a problem during the recruitment process. Therefore, the lack of extensive user data negatively influences later stages of the research when a deeper understanding of the contextual information is needed to adapt a robot companion behaviours to the user's needs during the interaction. A generic and resource-efficient solution to tackle this current problem would be beneficial to the HRI field and the future studies of our research. In this chapter, the development and the evaluation of an Activity Recognition System (ARS) is presented. It is based in a knowledge-driven approach and the evaluation was done through the *Experiment 1*. This work is supported by the publication Duque et al., see Appendix A. The creation of this system was a necessary step to take before embarking on the investigation of the personas technique (Duque et al. 2013a).

Diverse methodologies can be followed when creating an activity monitoring system for a smart environment, e.g. (Chen et al. 2012) (He et al. 2007) (Chua et al. 2009) (Storf et al. 2009) (Steinhauer et al. 2010), but the reduction of the data collected prior to the system evaluation must be considered as the biggest concern when developing a solution to match this research purposes. Based on that, a knowledge-driven methodology (Chen et al. 2012) (Storf et al. 2009) was adopted to design and develop a generic high-level ARS. The system is used to monitor the activities performed by participants during experimental trials and to extend the amount of data collected during HRI studies in the UH Robot House. This methodology avoids extensive data collection experiments to train the system. At the same time, it increases the context awareness of the system so that it is possible to understand and interpret the current activities performed and adapt the system's responses accordingly.

Understanding a user's activities at home is a first step to achieve the mentioned

Figure 3.1: Inside the UH Robot House view - Source: `http://adapsys.cs.herts.ac.uk/images/gallery/picture_gallery/robothouse-2.jpg`

social skills and expected behaviours from a robot companion when cohabiting with a human in the same space. Therefore, it was essential to provide the current UH Robot House system with extra functionality to increase the context awareness. Having a robot able to recognise the current user activities and adapt its behaviour accordingly can be considered a primary goal towards a social interaction between a human and a robot. In addition, creating a generic and knowledge-base system contributes to the research goal of reducing the user data collection needed to train the HRI system prior the first interaction. This was one of the main reasons to create the ARS for Activities of Daily Living (ADL) and integrates it into the UH Robot House so the overall information gathered and the system's performance could also be improved. The ARS defines a combination of primitive events (directly linked to an individual sensor) and high-level activities, i.e. daily routines defined by a sequential triggering of sensors, see Section 3.3.2. The knowledge-driven approach is based on the use of a natural language to define the rules detecting the activities during the interaction. This approach avoids the need of collecting participants' data before the experiment in order to train the system. The rules are based on the common-sense knowledge from the environment in combination with the sensor installed.

Therefore, during the first year of this research, the main task was to develop the activity recognition module to identify individual users' activities of daily living at the UH Robot House. The ARS developed and integrated into the current system was built on top of the installed GeoSystem (*GEO: Green Energy Options* n.d.), an electric power consumption monitoring system, and the ZigBee (Farahani 2008) sensor networks, further technical information can be found in Appendix B. Sensors from both sensor networks are installed around the house's facilities as shown in

Figure 3.1. These sorts of sensor networks provide a non-intrusive and easy-to-install solution to monitor activities at home. The sensors are typically a plug adapter that measures the current usage of an electrical appliance, or a magnetic switch that can be installed in cupboards or doors around the house. The combination of both types of sensors is used to infer participants' activities when using the facilities provided at the UH Robot House. The ARS created was responsive enough to interpret the data collected from both networks and determine in near-real time the tasks being performed by participants during experiments. In addition, it is worth to mention that the system was also used in another study performed in our department (Lehmann et al. 2013), and the data collected during the evaluation study was used by Saunders et al. to automatically derived rules to detect human activities at the UH Robot House (Saunders et al. 2016). The *Experiment 1* was performed under Ethic Approval protocol number 1112/39.

3.2 Activity Recognition System Questions and Goals

The purpose of this study was to develop and evaluate an ARS system in the UH Robot House based on a knowledge-driven approach. As pointed out during the introduction, a functional solution to supply extra information about participants' current activities at the UH Robot House was missing. The robot companion could navigate through the house facilities and approach the human in order to estimate, using computer vision techniques, the most likely activity being currently executed, however, this estimation cannot be guaranteed without a confirmation from additional sensors or the researcher supervision. The combination of the installed ZigBee and GeoSystem sensor networks created a great opportunity to develop the presented ARS in order to enhance the HRI studies performed in the house. Thinking about this research overall goal, the improvement of the system's context awareness by inferring users' activities during the interaction was a necessary step before delving into the investigation of the personas technique. In order to measure the success of this approach, the followings ARS questions were defined to guide this study and evaluate the data during the analysis stage:

- Q1. Is our ARS generic enough to detect different users' activities without the system being individually trained for the users?
- Q2. Can the ARS achieve an accuracy higher than 80% in the controlled experiments?
- Q3. Can the ARS achieve an accuracy higher than 80% in the unrestricted experiment?
- Q4. What are the advantages and disadvantages of the ARS presented in this thesis?

The system will be evaluated in two different sessions, a controlled and an unrestricted scenario, as it will be presented in section 3.4. The accuracy percentage defined in questions 2 and 3 was guided by a similar approach carry out by Kleinberger et al. prior to this investigation (Kleinberger et al. 2009). This value ensures a reasonable reliability of the activities detected, and thus the contextual information that is sent to the robot companion. Therefore, this percentage, 80%, will cover the system's confidence expectations, and reasonable errors produced whilst the identification of activities can be handled during the interaction by the robot companion own capabilities. For instance, the robot companion can also utilise information provided by the user during the interaction, or any of the onboard sensors installed into the robot. The comparison between the activities recognised by the system, and the observed activities performed by the user during the *Experiment 1* session, would determine the accuracy level of the system and its capacity to detect participants' activities during HRI studies. Therefore, the additional information provided by the ARS is expected to improve the robot's awareness of the situation and thus further enhance its abilities during the interaction with users in the domestic environment.

3.3 Sensor Network Description

The ARS developed and integrated into the UH Robot House, makes used of the two mentioned sensor networks, GeoSystem and Wireless ZigBee Sensor System, to determine the current activity performed by participants during HRI studies. The combination of sensors from both systems allows the detection of open drawers or doors, occupied chairs, sofa seat places, open water taps in the bathroom or the kitchen and any of the electrical appliances connected to the GeoSystem network at the time that those are activated or deactivated.

The first system, GeoSystem, provides the current voltage for the selected appliances installed around the Robot House. The appliance current is detected so it can be inferred when an electrical device is switched on or off, although in particular situations it is necessary to implement a more complex logic to reliably get the current value of particular appliances, e.g. the fridge's consumption difference between the engine or the internal light bulb. A total of 19 different electrical devices' power consumption are connected to the database managed by the GeoSystem API. The network refreshes all sensors' values each second (1Hz), so small delays can be expected when detecting the status of the sensors.

The second system, Wireless ZigBee Sensor System, is composed of reed contact, temperature and pressure sensors. The device named XBee Gateway X4, see Figure 3.2, forms the interface between the wireless ZigBee network and the wired Ethernet network. A total of 40 sensors are installed around the Robot House's facilities using five ZigBee modules to connect them, typically one module per room. All sensors information is sent to the centralised system every second. Depending on the kind of sensor and its characteristics, this returns different types of values, binary or digital. This network also refreshes all sensors' values each second, so small delays can also be expected. A technical report about the ZigBee sensor network and the GeoSystem's sensors is available in Appendix B.

Combining all sensors from both systems, a total of 59 sensors are available to be used by the ARS when detecting activities of daily living as described in the next section, see 3.3.2. A diagram showing the location of these sensors around the UH

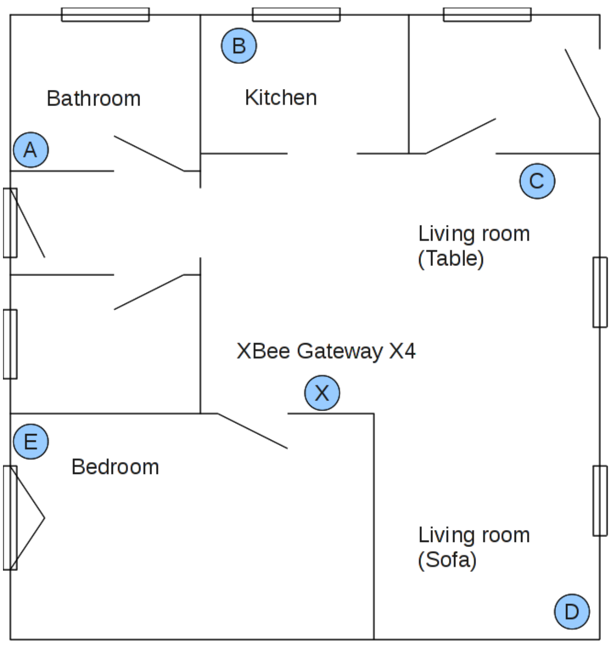

Figure 3.2: ZigBee Modules location in the Robot House

Robot House ground floor can be found in Figure 3.4. Following a summary of the types of sensors and the number of them installed across both systems:

- 19 electrical energy monitoring devices for electrical appliances and main lights installed around the bedroom, the living room, the kitchen and the hall entrance (GeoSystem).
- 26 reed contact pairs installed in doors and drawers in the kitchen, the bedroom, and the dining room facilities (ZigBee).
- 4 temperature sensors to detect changes in the temperature of the cold and hot water pipes of the bathroom and kitchen sink (ZigBee).
- 10 pressure mats to detect the usage of chairs at the dinning area or the bedroom and the sofa seats in the living room area (ZigBee).

3.3.1 System Development

In order to integrate the sensors' data and the ARS at the Robot House, a Java (*Java SE APIs & Documentation* n.d.) application connected to a MySQL 5.5 (*MySQL Documentation* n.d.) database was developed to gather, process and display the data supplied by the ZigBee and the Geo-System sensor networks. Based on the definition of rules, which will be specified in section 3.3.3, the system is able to infer the current activities performed by a single user in the house with an accuracy over 80% threshold previously defined (Duque et al. 2013a). The current context, sensors and activities activated in the system will be stored in a dedicated database, where the current context information will always be available to other modules of the system when this information is required. The ARS consists of four main modules, including the user interface, although this can be considered an extra feature of the system for visualisation purposes. A high-level representation of the architecture can be found in Figure 3.3 where the main modules defined are depicted and how those are interconnected.

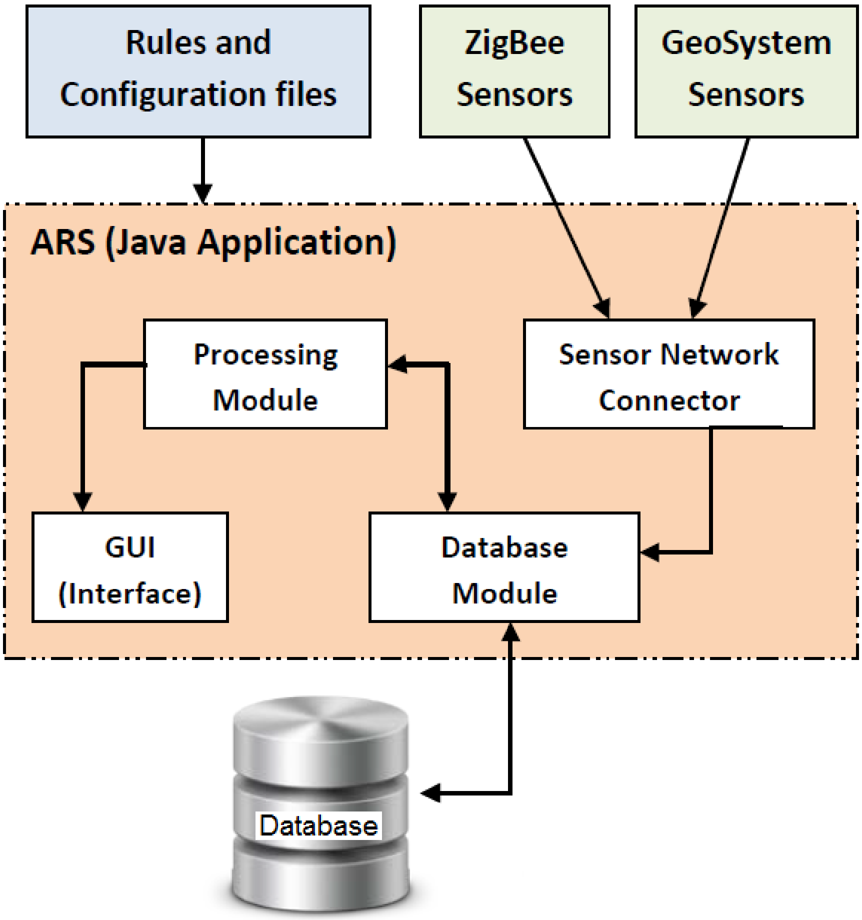

Figure 3.3: Activity Recognition System Architecture

- Sensors Network Connector
  - Collection of all data broadcast by both sensor networks, ZigBee and GeoSystem.

  - Filtering, calculating and transferring sensors' data into the database module.

- Database Module
  - Inserting and updating sensors' values into the database table defined for this purpose.
  - Retrieving sensors' latest values as requested by other components of the system.
  - Updating the current status of the activities defined into the system (see section 3.3.2).

- Processing Module
  - Request all sensors' values from the database module to determine if any of the activities defined in the system were activated or deactivated. This evaluation is based on the data collected plus the set of rules defined and supplied to the system through the rules file. This module's output is the group of all activated activities and the current status of the system is shown in the ARS GUI defined. The information gets updated into the database every second, so we need to consider this delay during the detection of the activities.

- Sensor Network Interface (GUI)
  - The interface presents a formatted view of all sensors' values, including both sensor networks, over the Robot House map. The interface automatically reloads all data every second, and updates the sensors' background colour (red or green) to ease the recognition of changing values.

It is worth to mention that the latest version of the ARS was integrated into the ACCOMPANY project's architecture (*ACCOMPANY: Acceptable robotiCs COMPanions for AgeiNg Years* 2011-2014). The updated version used the centralised database defined during the project to read and update the sensors values, as well as update the activities detected. This integration allowed the system to be used during different HRI studies performed at the UH Robot House, in addition to this research studies, adding extra value to the investigation presented in this chapter.

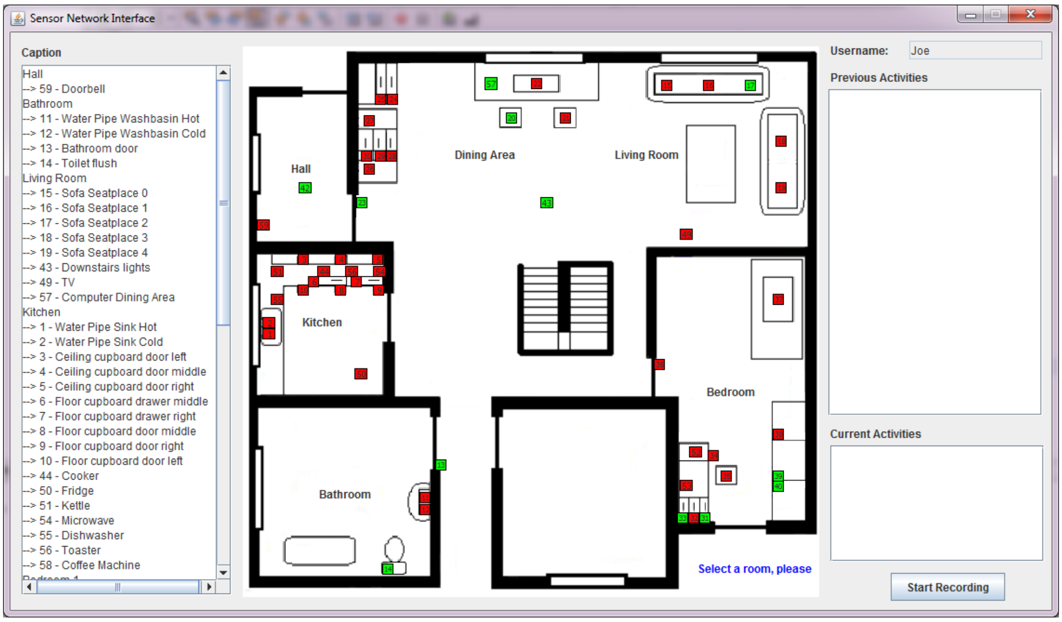

Figure 3.4: ARS Graphical Interface - Sensors installed around the Robot House

The Figures 3.4 and 3.5 show the ARS GUI and the current sensors' layout. The current status of each sensor is represented by the colours green, red or grey, which represent *ON*, *OFF* and *Disconnected* respectively. When selecting one of the rooms on the map, all sensors' info and values for this room are shown, see Figure 3.5. The information shown is retrieved from the database every second, which is sufficient to get a near-real time update about the current status of the system.

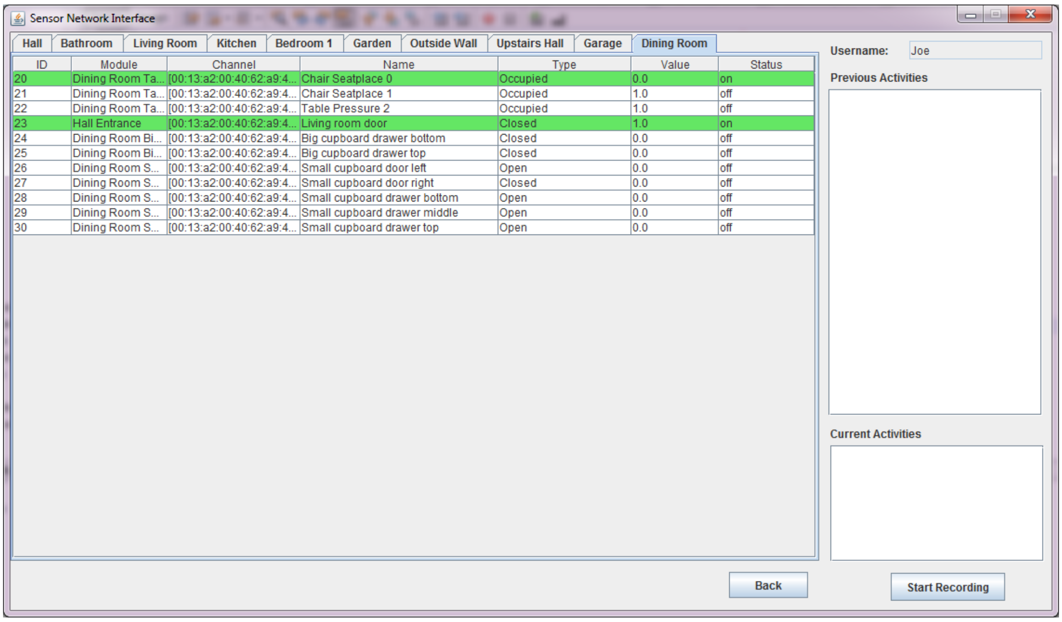

Figure 3.5: ARS Graphical Interface - Detailed description of the sensors per location

Below, the main database tables used in the system to store the sensors' data and update the status of the activities recognised. As stated before, MySQL was used as the database management software for the ARS. The table "Sensors" contains all information necessary to infer activities based on the latest status of individual sensors. The "UserActivities" table just stores the basic information about the activities being detected, in addition to their last time activation and deactivation, see Code 3.1.

Code 3.1: MySQL Tables Definition - *Sensors* and *UsersActivities*

```
CREATE TABLE `Sensors` (
  `sensorId` int(11) NOT NULL COMMENT 'Sensor Id',
  `value` text NOT NULL COMMENT 'Current sensor value',
  `locationId` int(11) NOT NULL COMMENT 'Sensor location ',
  `name` text NOT NULL COMMENT 'Sensor name',
  `sensorAccessPointID` int(11) NOT NULL COMMENT 'Technical access details',
  `sensorRule` text NOT NULL COMMENT 'Rule for interpretation',
  `ChannelDescriptor` tinytext NOT NULL COMMENT 'Technical channel',
  `sensorTypeId` int(11) NOT NULL COMMENT 'Link to sensor type',
```

```
  `lastUpdate` datetime NOT NULL COMMENT 'Last time this sensor was updated',
  `lastTimeActive` datetime NOT NULL COMMENT 'The last active time of the sensor',
  `lastActiveValue` text NOT NULL COMMENT 'The last active value of the sensor',
  `status` text NOT NULL COMMENT 'The status value e.g. on/off',
  `lastStatus` text NOT NULL COMMENT 'Last status read for the sensor',
  PRIMARY KEY (`sensorId`)
);


CREATE TABLE `UserActivities` (
  `id` int(11) NOT NULL,
  `name` varchar(45) DEFAULT NULL,
  `status` int(11) DEFAULT NULL,
  `lastTimeActive` datetime DEFAULT NULL,
  `lastTimeDeactivation` datetime DEFAULT NULL,
  PRIMARY KEY (`id`)
);
```

3.3.2 Activities of Daily Living in the Robot House

A set of activities of daily living was defined for recognition in UH Robot House. The sensor networks' capabilities to detect user activities drove the definition of these activities in the system. Previous knowledge from HRI studies done at the UH Robot House helped to understand on the set of activities that would add more value to the final research goal of integrating the personas technique into a computational behaviour model for HRI studies. The activities were detected through a combination of individual sensors triggered in the environment, and in some cases, through the combination of a set of activities previously detected in the environment, called context-activities. Each of the sensors that determines the status of an individual electrical appliance, door or cupboard can be defined as a primitive action in the system. Therefore, more complex activities of daily living are detected by the combination of one or more primitive actions and other sensors used for the detection of this activity, e.g. *Watching Television* is a combination of the television being switched on and the user being sat on the sofa, which is detected by individual pressure mat sensors.

Following this principle, there is a wide variety of activities that could be defined and the expansion of the current sensors installed around the house would probably increase the number of activities to be defined. In addition, using a natural language to define activity rules provides the possibility to easily define and modify the set of initial rules as new activities patterns are detected in the environment. The set of activities to define should be based on the common-sense knowledge of the environment where the HRI studies are going to take place, in our case the UH Robot House. For instance, preparing breakfast is the combination of opening the fridge, opening certain cupboards and using the toaster during the morning. In addition, the robot companions' capabilities to interact and react to the users' activities defined in the system must also be considered. The maximum number of activities to be recognised is limited to the sensors installed in the network and the combination of events that can be used to defined the activation of these activities. The set of activities defined was linked to the future stages of this research and how to enhance the HRI experiment to be performed. This is the summary of the main activities and primitive actions (individual sensors):

- The user preparing some food in the kitchen.
- The user preparing a hot or cold drink in the kitchen.
- The user having a meal in the living room or dining area.
- The user laying the table in the living room or dining area.
- The user clearing the table in the living room or dining area.
- The user watching television in the living room.

- The user using the computer in the living room or dining area.
- The user reading or playing video games either in the living room or dining area.
- The user using the toaster, kettle, computer, television or fridge (primitive actions).
- The user sitting on the sofa or dining area chairs (primitive actions).

In order to have a better understanding of how an activity can be defined, a couple of examples combining primitives actions and context-activities are presented. For instance, *Having a Meal in the Living Room* is the combination of *Preparing some Food* and *Sitting on the Sofa Area* when those are activated in a temporal sequence. In addition, the detection of the activity *Preparing some Food* is the combination of several individual sensors from the kitchen activated in a temporal sequence. The activities defined are normally related to tasks where our robot companion can assist users. Sunflower (see Section 4.5 for further details), is a robot companion capable of carrying small objects between different areas inside the UH Robot House, remind tasks to the user, and alert the user about unexpected events regarding electrical appliances.

3.3.3 Rules and Algorithm Definition

The definition of rules explicitly represented makes the activity rules definition more understandable for non-experts user of the system. This is one of the main advantages of the ARS defined, the natural language used to define semantic rules and the ability to modify these rules based on the combination of the sensors available in the domestic environment where the ARS was installed. In this section, we describe the rules definition using a couple of activities detected in the system as an example. As mentioned above, certain activities are just associated with a single sensor in the network, primitive actions. This distinction between a sensor and a primitive action helps to detect other activates as the sensor defined as a primitive action can now be included as part of the context-activities in the activity rule definition. The main advantage is that a context-activity can happen in a time window defined, while a sensor can just be activated or deactivated without considering a time window. For the definition of rules, the following tags are used to specify the sensors, context-activities or other parameters and values that used to trigger the recognition of each of the activities defined in the system.

- Duration: The maximum time the activity remains activated in the system. Some activities, e.g. *Using Computer Dining Area*, see Code 3.2, do not consider this tag as they are deactivated based on their associated context-activities or sensors' status values.

- Location: The location where the activity is performed. This is used for descriptive purposes only.

- Context: Set of activities that has to be fulfilled before the activity is activated. Some activities, e.g. *Sitting Living Room*, could not define any context-activity associated with them. *Interval*: Time window in which the context-activity is relevant for the detection of the activity. *Status*: The required context-activity's state for the activation of the activity.

- Threshold (Sensors' attribute): Minimum value necessary to consider the activity as activated. It is based on the accumulated weight of the sensors triggered.

- Sensors: Each of the sensors directly involved in the detection of the activity. They have the *Status*, the *Obligatory* (True: The sensor's weight is added to the accumulated activity weight when the the sensor is activated, otherwise, its weight is subtracted from the accumulated weight; False: the sensor's weight is added to the accumulated weight when it gets activated, but its deactivation does not alter the accumulated weight), and the *Weight* fields. The sensors tag does not need always to be populated as an activity rule can be just defined with context-activities if necessary.

In Code 3.2, two rules examples were included, *Using Computer Dining Area* and *Preparing Hot Drink* to illustrate the process of defining a rule. More rules definitions can be found in the author GitHub repository (*ARS Rules Definition - GitHub* 2016). For instance, in order to detect a participant using the computer in the dining area, the *Computer ON* event, and the user sits in the dining area chair, *Sitting Dinning Area*, have to be recognised simultaneously in order to trigger the detection of *Using Computer Dining Area*. Notice that the status of both context-activities is set to "activated" which means that the activation and deactivation have an immediate effect on the status of the activity to be triggered. This is the reason *Duration* is not defined for this particular activity rule definition.

In our second example, *Preparing Hot Drink*, the activity gets triggered in the system once the threshold defined in the rule is reached. Each of the sensors defined inside the activity rule has a weight associated which represents how important this sensor is for the activity in order to successfully recognise it. Once the defined activity is activated this will remain as such in the system for the *Duration* defined, in this case, 300000 ms or 5 min. This activity does not require any context-activity for its detections, as opposite to the previous example.

Code 3.2: Rule Definition Example

```
<Activity Name="Using_Computer_Dining_Area">
    <Duration>Nil</Duration>
    <Location>Dining_Area</Location>
    <Contexts>
      <Context Interval="0" Status="activated">Sitting_Dining_Area</Context>
      <Context Interval="0" Status="activated">Computer_ON</Context>
        </Contexts>
        <Threshold>0.0</Threshold>
        <Sensors></Sensors>
 </Activity>

 <Activity Name="Preparing_Hot_Drink">
    <Duration>300000</Duration>
    <Location>Kitchen</Location>
    <Contexts></Contexts>
    <Threshold>0.5</Threshold>
    <Sensors>
      <Sensor Status="on" Obligatory="false" Weight="10">WaterPipeSinkHot</Sensor>
      <Sensor Status="on" Obligatory="false" Weight="10">WaterPipeSinkCold</Sensor>
      <Sensor Status="on" Obligatory="false" Weight="20">CeilingCupboardRight</Sensor>
      <Sensor Status="on" Obligatory="false" Weight="20">FloorCupboardRight</Sensor>
      <Sensor Status="on" Obligatory="false" Weight="10">Fridge</Sensor>
      <Sensor Status="on" Obligatory="false" Weight="30">Kettle</Sensor>
    </Sensors>
  </Activity>
```

Following the Pseudocode description, (Furman n.d.), of the algorithm used to activate and deactivate activities in the system, see Code 3.3. The Java code of this algorithm can be found on the author GitHub repository (*ARS Main Algorithm - GitHub* 2016). This algorithm is able to infer activated, deactivated and partially activated activities based on the parameters defined for each activity inside the activity rules configuration file. Every time that the activity's status changes the system gets updated and the information is stored in the database, so the rest of system's components can access this new information.

Code 3.3: ARS Main Algorithm - Activities Recognition Logic

```
VECTOR _activitiesDefinition;
VECTOR _activatedActivities;
VECTOR _partialActivatedActivities;
VECTOR _pastActivities;

VOID ARSAlgorithm (STRING sensor, SENSORPROPERTIES sensorProp) {
    FOR EACH activity IN _activitiesDefinition
        Check Overtime NonActivatedActivities;
        Check Overtime ActivatedActivities;
        IF activity->sensorList IS empty
            IF contextFilter(activity)
                _activatedActivities.add(activity)
            ELSE IF _activatedActivities.contains(activity)
                fromActivatedToPastActivity(activity);
            END_ELSE_IF
        ELSE IF activity->existSensor(sensor)
            IF sensor->status == previousStatus
                IF _activatedActivities.contains(activity)
                     Update _activatedActivities;
                ELSE IF _partialActivatedActivities.contains(activity)
                     Update _partialActivatedActivities;
                ELSE
                     _partialActivatedActivities.add(activity);
                END_ELSE_IF
            ELSE
                IF sensor->obligatory == true
                    IF _partialActivatedActivities.contains(activity)
                        _partialActivatedActivities.delete(sensor);
                        Update _partialActivatedActivities;
                    ELSE IF _activatedActivities.contains(activity)
                         _activatedActivities.delete(sensor);
                         Update _activatedActivities;
                    END_ELSE_IF
                END_IF
             END_IF
        ELSE
            Check Context and Update _activatedActivities;
            Check Context and Update _partialActivatedActivities;
        END_ELSE_IF
    END_FOR
}
```

3.4 Experimental Design and Procedure

A validation experiment, *Experiment 1*, was conducted in the UH Robot House in order to measure the reliability and accuracy of the ARS in both a controlled and an unrestricted scenario. A sample of 14 adults, aged between 23 to 54 years old, was recruited from different departments at University of Hertfordshire. The sample got a reasonable balance between gender and background among the participants recruited. All the subjects completed a consent form prior to the experiment, in which they were informed about the voluntary nature of the experiments. The two scenarios were run on two different days, and users were informed about this fact, as well as the time required for each session, approximately 20 minutes. For further information about the consent form see Appendix C.1.

3.4.1 Experimental Setup

The experiment took place in the UH Robot House, where the sensor network and the prototype activity recognition software were installed. All the experiments were video recorded using two different cameras (see Figure 3.6). One camera covered the dining and living room areas, and the other the kitchen area. These rooms were the only rooms that participants used during the whole execution of this study. In order to set the same environment for all participants, the cupboards were labelled to ensure that everybody knew the location of cutlery and objects inside the house facilities. This made the study more realistic as users did not spend too much time looking for objects around cupboards, so they were expected to act similarly to how they act in their own houses.

The ARS generates two different log files for each of the sessions run. The first file stores all the sensors activation and deactivation during the experiment, as well as the activity recognition algorithm logs and how the decision is made in real time. The second file represents the raw sensory data received from both sensor networks during the experiment. As mentioned before, the system is not currently able to recognise the full range of activities that participants could perform at home. This limitation comes from the number and types of sensors installed in the house. For this reason, the evaluation process was restricted to the set of activities described in the Table 3.2. These activities were selected based on the UH Robot House companion capabilities to assist participants during the future studies of this research.

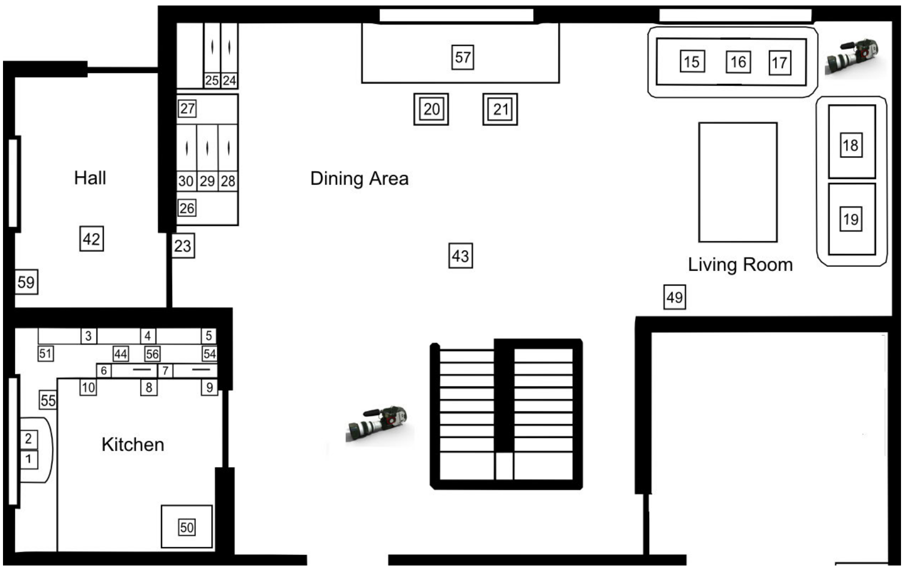

Figure 3.6: UH Robot House map representing the experimental area, ARS's sensors location and cameras position.

3.4.2 Participants

A total of 14 participants (4 female and 10 male) took part in the *Experiment 1* carried out at UH Robot House. The participants were asked to perform as if they were in their own house during the experiment, trying to make them feel as comfortable as possible. They were allowed to use any of the resources located at the UH Robot House experimental area, so no particular restrictions were made. The demographic data has been summarised in the following table (see Table 3.1):

Variables	**Value**	**N(14)**	**Percentage**
Gender	Male	4	29%
	Female	10	71%
Age	Under 30	8	57%
	30-45	5	36%
	Over 45	1	7%
Background	Technology Related	10	71%
	Non Technology Related	4	29%
Previous Experience in the Robot House	No	9	64%
	Yes	5	36%

Table 3.1: Summary table - Demographic data from our sample (N=14) in the *Experiment 1*.

As mentioned above, all participants were recruited from the University of Hertfordshire and the local area. Gender or age-related differences were not particularly investigated when interacting with companions, so this sample is a mixture of ages, genders and technical backgrounds without following any particular pattern. As the majority of participants were no older than 30 years old, it can be assumed that they are exposed to technologies on a daily basis. This reason should be taken into consideration when interpreting the results of this investigation and its limitations.

3.4.3 Experimental Procedure

As mentioned above, a two-days experiment was performed by all participants. In the first session, the main researcher briefly explained the experimental procedure and introduced the house's facilities to each subject prior to the beginning of the first session. After filling in the consent form and some basic demographic information was collected, participants were asked to perform a set of individual ADL's, see *Activities Script* in Appendix C.1, on their own and using the UH Robot House's facilities in the way that they felt more comfortable with. The main researcher was in the same room as the participant during this session and was guiding the user just at the beginning of each task. The purpose was to check the system accuracy in a controlled environment, where just one activity was completed at the time and supervised by the main researcher.

In the second session, the participants spent approximately 20 minutes on their own simulating living in the house. This time, the main researcher was in a different room during the performance of the session. Participants were told to perform whichever activity they wished, based on the set of activities already presented during the first session, and without following any particular pattern. Depending on the time of the day, a breakfast or a lunch time scenario was defined to situate participants during the session. They were totally free to prepare their breakfast or snack if they wished to do so. In this occasion, the ARS was exposed to a more complex situation where activities could happen in parallel or in a different order to the one that could has been thought during the definition of the system. These two different sessions, controlled and unrestricted, helped measure the system's accuracy and check its reliability in a realistic environment. After each session, the participants were asked to complete a short questionnaire to rate their overall feeling about the scenarios and the activities performed.

3.5 Analysis and Evaluation

3.5.1 Behaviour coding

For the analysis of data, all the activities performed by the participants were coded using a commercial software available for this purpose. The Observer XT, by Noldus Information Technology (*Noldus Information Technology. The Observer XT Software* n.d.), was used for coding, analysing and presenting the observational data. This software allowed the definition of the coding scheme to be used and the extraction of the participants' actions during both experimental sessions. Examples of behaviour coding studies can be found in the HRI field, e.g. (Koay et al. 2006), and the Psychology field, e.g. (Flenthrope & Brady 2010). Following this approach, each session was individually analysed and the important events were identified.

Two coders, the main research and one external observer trained for this purpose, were independently coding the activities performed by each of the participants. Before the video coding process began, both coders were familiarised with the coding scheme shown in Table 3.2. The first coder coded all videos and activities from both sessions, and the external observer just coded 10% of the videos. Standard practice in the literature has been to code between 10% and 25% of all observations for observer agreement (Haidet et al. 2009). In order to obtain from the Observer software a list of events similar to the event list generated by the sensor network during the experiment, both observers were asked to code just the activities where users interacted with the sensors installed in the network. Otherwise, it would have been difficult to match both event lists during the analysis of the data. Using the feature provided by the software each individual event chart was generated for visualisation purposes (see example Fig. 3.7). In this example, the activities *Having Meal*, *Spare Time* and *Sitting in the Living Room* were simultaneously and successfully recognised for the participant.

3.5.1.1 Inter-rater Reliability Test

The Cohen's kappa coefficient statistic measure (Sim & Wright 2005) was used to determine the level of agreement between the two different coding outputs generated by both coders. The observations were paired in the analysis tool offered by the

Code	Behaviour	Description
ut	Using Toaster	The time that this appliance is switched on
uk	Using Kettle	The time that this appliance is switched on
pf	Preparing Food	The user is in the kitchen preparing some food
pcd	Preparing Cold Drink	The user is having some cold beverage
phd	Preparing Hot Drink	The user is preparing either tea or coffee
co	Computer ON	The time that this appliance is switched on
uc	Using Computer	The user is sitting in the dining area and using the computer
sd	Sitting Dining Area	The user is sitting in the dining area
lt	Laying Table	The user prepares the table before having meal
md	Having Meal Dining Area	The user is sitting in the dining area and having mea
std	Spare Time Dining Area	The user is reading a book or newspaper in the dining area
wt	Watching TV	The user is sitting in the living room and watching the television
t	TV ON	The time that this appliance is switched on
slr	Sitting Living Room	The user is sitting in the living room
stl	Spare Time Living Room	The user is reading a book or newspaper in the living room
ml	Having Meal Living Room	The robot reminds the user about some medicine
ct	Cleaning Table	The user finish the meal and tidy up all the objects used

Table 3.2: Behaviour Coding Scheme. Set of Activities Defined in our ARS.

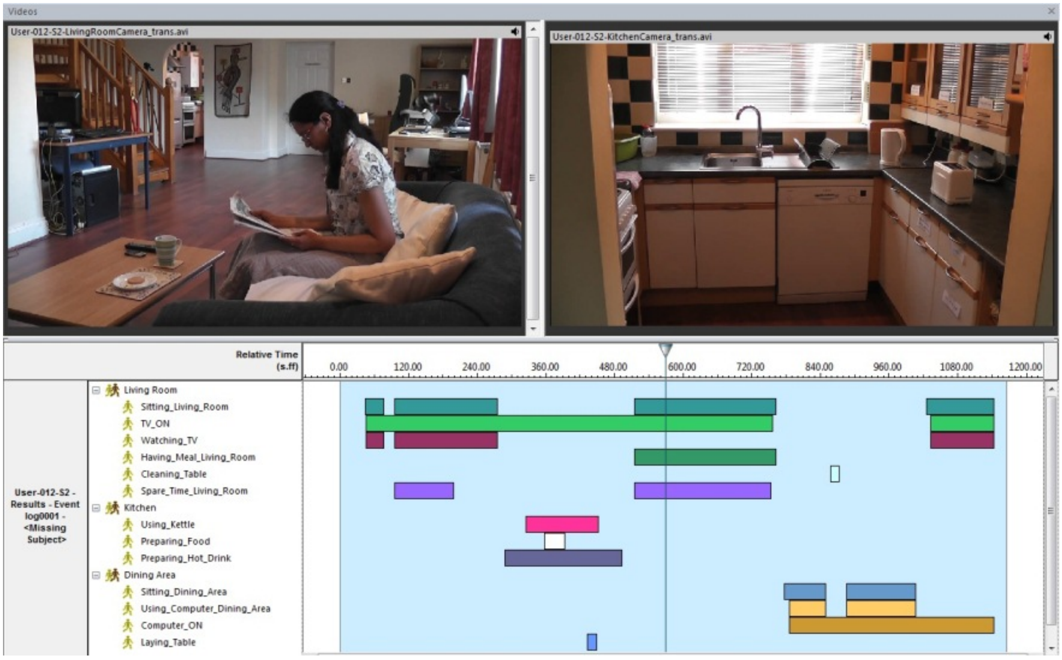

Figure 3.7: Cameras' view and coding visualization shown by The Observer XT software. The graph depicts the user's activities detected during the experiment.

Observer XT software, and the kappa value was generated automatically for both sessions. The time windows for the reliability analysis was defined as 1 second. The kappa value for the combined analysis was 0.75, with an overall agreement of 76%. This result represents a good agreement rate for both coding (Bakeman & Gottman 1997). This result is attributed to the unique way in which both coders can interpret the performance of the ADL's defined in the UH Robot House.

3.5.2 Data Analysis

The 14 participants' data for the two sessions were analysed to evaluated the accuracy and reliability of the system. Each session result is presented separately since each session was run in a slightly different format. The system performance was calculated in terms of precision, recall and accuracy (Olson & Delen 2008) over the entire sample (see Figure 3.8).

$$Precision = \frac{tp}{tp + fp} \qquad Recall = \frac{tp}{tp + fn}$$
$$Accuracy = \frac{tp}{tp + fp + fn}$$

Figure 3.8: Precision, Recall and Accuracy formulas. (tp = true positives or 'recognized', fn = false negatives or 'wrongly recognized' and fp = false positives or 'extra-recognized').

A spreadsheet file for each experimental session' data was created in order to pair the event list individually obtained from the video coding analysis and the ARS system. The combined result is depicted in Table 3.3. The left-hand side of the table represents the events exported from the Observer XT software after being formatted. On the right-hand side, the ARS activities list recorded, including their starting times. This was a visual way of presenting the data to easily identified recognised, wrongly recognised or extra-recognized activities. An activity is considered extra-recognized when its identification was correct based on the activity rule defined, but the participant was not actually performing this activity. As this is a valid activity to be recognised, it could be executed on a different time, this cannot be considered as an error. Following the data analysis for each of the sessions performed.

3.5.2.1 Session 1

During the first session, the main research led the participant throughout the activities to be performed. A total of 240 events were coded between all the participant's experiments carried out in this session. The average number of recognised activities

Observation	Time_Relative_hms	Duration_sf	Behavior	Event_Type		System	System Events	Time	Time Relative	Delay (seconds)
								08:21:35		
User-001-S2	00:00:00	60.74	Preparing_Cold_Drink	State start		Yes	Preparing_Cold_Drink	08:22:18	00:00:43	00:00:43
User-001-S2	00:00:05	299.88	Preparing_Food	State start		Yes	Preparing_Food	08:21:39	00:00:04	00:00:01
User-001-S2	00:00:21	75.04	Using_Toaster	State start		Yes	Using_Toaster	08:21:58	00:00:23	00:00:02
User-001-S2	00:01:00	0	Preparing_Cold_Drink	State stop						
User-001-S2	00:01:28	16.96	Laying_Table	State start		Yes	Laying_Table	08:23:01	00:01:26	00:00:02
User-001-S2	00:01:36	0	Using_Toaster	State stop						
User-001-S2	00:01:45	0	Laying_Table	State stop						
User-001-S2	00:02:01	50.06	Using_Toaster	State start		Yes	Using_Toaster	08:23:36	00:02:01	00:00:00
User-001-S2	00:02:11	41.32	Sitting_Dining_Area	State start		Yes	Sitting_Dining_Area	08:23:45	00:02:10	00:00:01
						Extra	Having_Meal_Dining_Area	08:23:45	00:02:10	00:02:10
User-001-S2	00:02:16	897.78	Computer_ON	State start		Yes	Computer_ON	08:23:50	00:02:15	00:00:01
User-001-S2	00:02:16	36.82	Using_Computer_Dining_Area	State start		Yes	Using_Computer_Dining_Area	08:23:50	00:02:15	00:00:01
User-001-S2	00:02:51	0	Using_Toaster	State stop						
User-001-S2	00:02:52	0	Sitting_Dining_Area	State stop						
User-001-S2	00:02:52	0	Using_Computer_Dining_Area	State stop						
User-001-S2	00:05:05	0	Preparing_Food	State stop						
User-001-S2	00:05:25	376.12	Having_Meal_Living_Room	State start		Yes	Having_Meal_Living_Room	08:27:03	00:05:28	00:00:03
User-001-S2	00:05:25	154.68	Sitting_Living_Room	State start		Yes	Sitting_Living_Room	08:27:03	00:05:28	00:00:03
User-001-S2	00:05:48	131.92	TV_ON	State start		Yes	TV_ON	08:27:24	00:05:49	00:00:01
User-001-S2	00:05:48	131.92	Watching_TV	State start		Yes	Watching_TV	08:27:24	00:05:49	00:00:01
User-001-S2	00:08:00	0	TV_ON	State stop						
User-001-S2	00:08:00	0	Watching_TV	State stop						
User-001-S2	00:08:00	0	Sitting_Living_Room	State stop						

Table 3.3: The Observer XT formatted output (left side) and the activity recognizer's event logs (right side). This data representation helped us analyse the results and find behaviour patterns that will be considered in future works.

per participant was 17 activities. The overall number of activities correctly recognised was 239, with 1 missed activity and 37 extra-activities also detected. Based on the figures, a precision of 86,59%, a recall of 99,58% and an accuracy of 86,28% was achieved for the first session. In general, an acceptable delay was obtained when detecting the activities, but the most complex activities incurred in a bigger delay, i.e. those activities involving a major number of sensors to be recognised (e.g. preparing food or preparing a beverage). The rest of the activities were recognised with an average delay of two seconds, which is reasonably fast, taking into account the operating system frequency of 1Hz. The Figure 3.9 depicts the recognition delay observed per activity during the experiment.

After the experiment, a couple of questions using a 5-Likert scale were asked to participants about the overall feeling of the scenarios and how similarly they behaved compared to their own houses. These question were asked to check the naturally of the environment and experiment created for the participants. The frequency tables for this session have been depicted in the Figure 3.10 and the Figure 3.12. To the first question *How did you find the scenarios on home activities?* the participants' mode value achieved represented the answer *Quite Natural* with *(1=Very Natural - 5=Very Unnatural)*, and for the second question *Did you carry out the activities in the same way in which you behave usually in your own house/flat?* the participants' mode value achieved represented the answer *Quite Similar* with *(1=Very Similar - 5=Very Different)*. These results demonstrated that we created a relaxed environment for participants to performs the activities as they were in their homes.

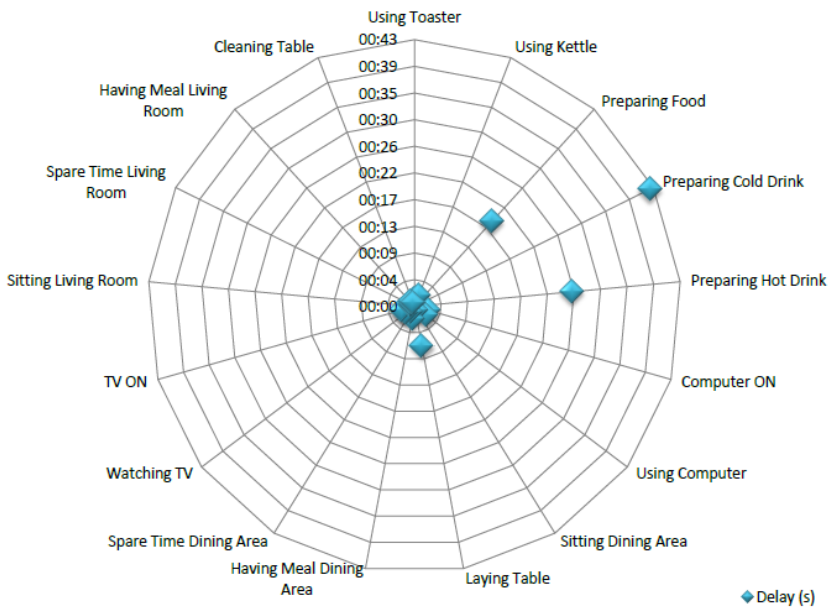

Figure 3.9: Overall recognition delay per activity in the controlled scenario.

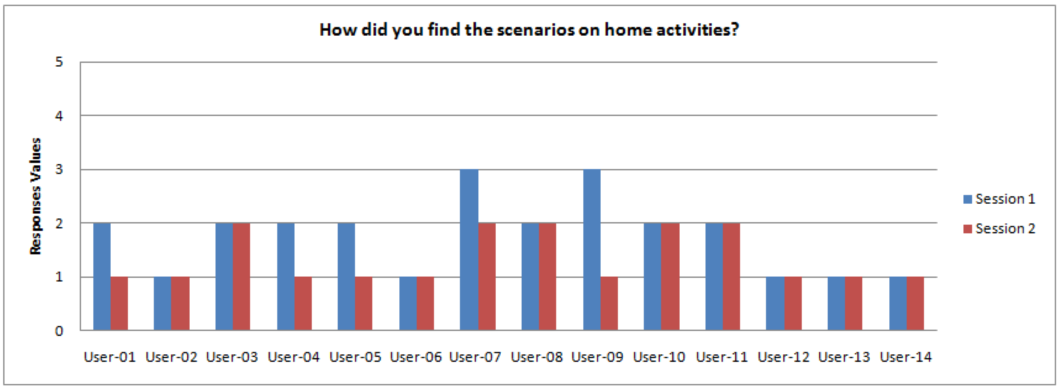

Figure 3.10: Frequency table for the session 1 and the session 2 to the question depicted in the chart.

3.5.2.2 Session 2

In the second session, a good overall result was also achieved, even considering the openness of the scenario which the system was exposed to. A total of 216 events were coded between all the participants' studies carried out in this session. The average number of recognised activities per participant was 15 activities. The number of activities correctly recognised was 200, with 16 activities being wrongly recognised and 23 extra-activities being triggered. Using this figures, a precision of 89,69%, a recall of 92,59% and an accuracy of 83,68% was achieved. As stated before, some delay were found on the most complex activities, e.g. *Preparing Food* was recognised with a delay of 35 seconds and *Preparing a Cold Drink* with a delay of 20 seconds. The rest of activities were recognised with the same average delay than in the first session, two seconds. The Figure 3.11 depicts the recognition delay observed per activity during the experiment.

Similarly to the first session, the same couple of question were asked during this session to check the naturalness of the experiment. The frequency tables for this session have been depicted in the Figure 3.10 and the Figure 3.12. To the first question *How did you find the scenarios on home activities?* the participants' mode value achieved represented the answer *Very Natural* with *(1=Very Natural - 5=Very Unnatural)*, and for the second question *Did you carry out the activities in the same way in which you behave usually in your own house/flat?* the participants' mode value achieved represented the answer *Very Similar* with *(1=Very Similar - 5=Very Different)*. These results demonstrated even further how comfortable users felt in the UH Robot House performing the study.

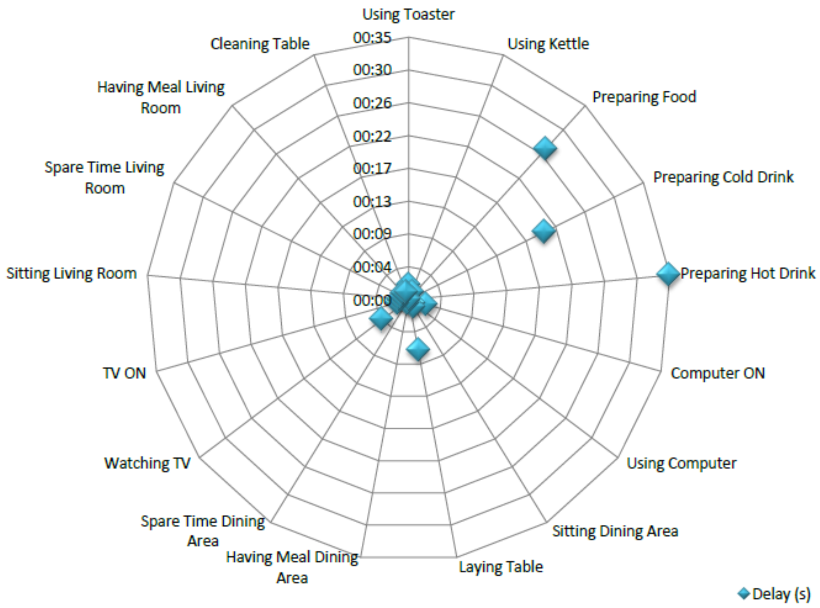

Figure 3.11: Overall recognition delay per activity in the unrestricted scenario.

Additionally, the participants were asked about the possibility of living with a robot companion in the future and the tasks in which they would like to be helped with. A total of 10 participants answered positively to the question of having a robot at home. On the other hand, 4 participants thought that they would be

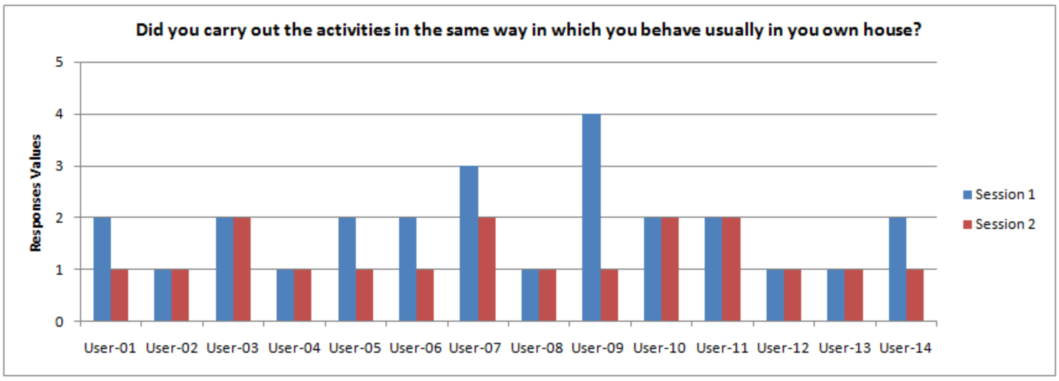

Figure 3.12: Frequency table for the session 1 and the session 2 to the question depicted in the chart.

better living by themselves unless assistant was really required due to some sort of disability. The participants answering positively the first question pointed some of the tasks in which they would like to be assisted in the future. These answers were really useful for the upcoming experiments of this research as they provided the sorts of tasks to be included in future experiments and understanding the needs of participants at home. The following table, Table 3.13, depicts the main tasks pointed by the participants and their frequencies. The author of this dissertation was largely enrich by this experiment and the knowledge collected after interacting with participants in the UH Robot House and knowing about their preferences living with robot companions at home.

3.6 Discussion and Limitations

In this chapter, the definition and the evaluation of a generic and resource-efficient ARS based on a knowledge-driven approach were presented. The methodology followed tackles directly one of the main problems pointed out in HRI studies, the time taken by participants to perform studies in order to collect data and train the system

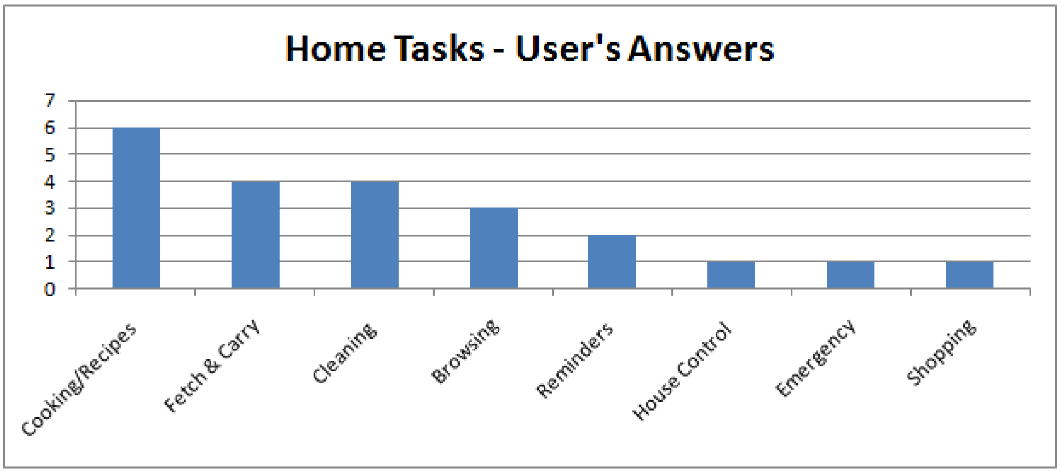

Figure 3.13: Frequency table for the tasks in which participants would like to be helped by a robot companion.

for the interaction. The creation and investigation of different approaches to cope with this issue is one of the main research goals, see Chapter 1. Based on the results of the system evaluation, the possibility of creating a human activity recognition system upon the knowledge of the system and sensors installed without individually training the system for specific users was demonstrated. This result positively answers the first question *Q1* of this chapter. The accuracy achieved in both the controlled and the unrestricted sessions exceeded the 80% threshold defined. This was considered adequate for the kinds of studies that we will be performed during this research and guided by similar studies (Kleinberger et al. 2009). The accuracy achieved allows us to positively answer the questions *Q2* and *Q3* of this chapter.

The ARS developed added a great value to the sensor network systems already installed in the UH Robot House. Several are the advantages of using these non-restricted and naturalistic system systems. For instance, the participants behaved as they would in their own houses, as reported after the evaluation of scenarios. In addition, they were not wearing any sensor and the system was not individually trained on previous data collected so participants were just required during the evaluation of the system. Another of the system advantages is the easy expansion and migration time, keeping the overall low-cost, resource-efficient system characteristics. Finally, the definition of semantic rules expressed in a natural language benefits any kind of user, from expert to non-experts, when the modification or the creation of a new rule needs to be built on the existing rules and sensors installed in the network.

On the other hand, the system does present some limitations and disadvantages. Firstly, the types of sensors currently installed in the system do not allow to accurately determine the location of the user in the house or associate a sensor activation with an individual. Therefore, the recognition of activities for two or more users simultaneously cannot be directly achieved without expanding the current sensor network. Secondly, the rules defined in the system lack a learning module to modify the initial set of rules and improve the system performance when an activity recognition pattern needs to be modified. This feature should be considered as future work of the ARS system presented. Finally, the current sensor network cannot be used to get a deeper understanding of the activities detected, i.e. when the user open the fridge to take a beverage, the ARS will detect the action of opening the fridge but it will not supply information about what the user actually did. This information could really useful to command robot companions to offer their help in certain situations and avoid interrupting the user in others. Nevertheless, human activity detection remains an open challenge for researchers all around the world and not just for HRI applications as pointed out by van Kasteren (Van Kasteren 2011).

In conclusion, a knowledge-based rule system to identify a user's activities in a home environment was presented. This approach was empirically evaluated by means of the *Experiment 1* carried out in this environment. The results achieved fulfilled the initial expectations and answered the questions defined in Section 3.2. These findings motivating to progress towards the final research goal of designing social, context-aware robot companions able to adapt their behaviours to a user's need and preferences prior to the interaction. The ARS was integrated into the UH Robot House system and later modified to support the requirement of the ACCOMPANY project (*ACCOMPANY: Acceptable robotiCs COMPanions for AgeiNg Years* 2011-2014), so the system could also be used in future experiments in our research group.

Chapter 4

A Different Approach Using Personas in Human-Robot Interaction

4.1 Introduction

As presented in the literature review, the field of HRI faces great challenges ahead. The introduction of robot companions in people's houses should come with the integration of social skills into robots so that they could be accepted by humans. However, the achievement of this task will require large amounts of data to train the system before being able to validate that these social skills implemented into robots are the accepted and the ones expected by users. The novel approach to be investigated in this dissertation tries to close the gap between the design of a robot companion and the adaptation of its behaviour to the user's characteristics and preferences when first interacting. In addition, the integration of the personas technique into a computational behaviour model is expected to reduce the burden put on participants when user data is required to trained each individual robot feature in order to improve the adaptability of the HRI system.

An initial set of personas has been supported by the knowledge collected in the Adaptive Systems Research group when investigating several topics (*COGNIRON: The Cognitive Robot Companion* 2004-2007) (*LIREC: Living with Robots and Interactive Companions* 2007-2013). The matching between a user of the system and the pre-defined personas will characterise the way in which robot companions will behave during the first interaction. The creation of a computational behaviour model will help modify robot companions behaviours during the performance of the HRI study in order to enhance the interaction between the user and the robot by adapting the system to the user's needs and characteristics. The definition of a general behaviour model in the field of HRI to adapt robot behaviours to different types of users is still an open challenge that needs to be addressed. This investigation will demonstrate whether the personas technique integrated into a computational model could be a useful approach to adapt robot companions during the interaction and improve their social skills during the first encounter with humans. The HRI field will benefit from investigating this technique to be directly applied to the designing and the development of robots in a domestic environment. This chapter's content is supported by the publication Duque et al. (Duque et al. 2013b), see Appendix A.

This chapter presents the steps to be followed during this investigation in preparation for the upcoming chapters where two different studies, *Experiment 2* and *Experiment 3*, will be manifested. In the following sections, the first set of personas will be presented based mainly on findings from a previous related experiment carried out in our department before this research was conducted. This experiment provided sufficient information for the creation of the first two personas to be integrated in the model being investigated. During this chapter will also describe the robot features that should be modified in order to adapt the robot behaviour to the participants, and how these features are associated to the personas defined. The section 4.4 will present the definition of the architecture to integrate all modules and the model resulting from this investigation. The first research question RQ1: *"Which system architecture should we define in order to create a computational system able to automatically adapt a robot companion's behaviour to users based on their needs?"*, will be answered once the system is proven successful for the purpose it was defined. This architecture should ease the task of adapting the robot behaviour to the user characteristics during the first encounter. In the last section of this chapter, the methodology and evaluation approach used will be presented. The main reason to follow an iterative methodology is the possibility of evolving the initial computational behaviour model. Based on the findings after each of the studies to carried out at the UH Robot House, the system will be evolve from its initial definition.

4.2 The Personas Initial Definition

The personas technique was developed based on the understanding of users' needs and goals in order to adapt the system to their characteristics (Cooper et al. 2007) (Nielsen 2012). In HCI, the technique is used to guide the design and development process of a product and to ensure that the final product developed meets the user's requirements (Pruitt & Grudin 2006). Both research fields, the HCI and the HRI, share a common task of being focused on human interactions with computational technology. As Reeves et al. and Nass et al. pointed out during their investigations, users tend to develop social relationships with computers even when they are aware of the unnaturalness of computers (Reeves & Nass 1996) (Nass et al. 1994). Based on the links between both fields, humans could be expected to develop the same relationships towards robot companions when co-habiting in the near future. This will make the robot environmental adaptability to play a fundamental role on the user's acceptance during the interaction. In the attempt at integrating the personas technique and investigating its benefits inside the HRI field, a deeper understanding will be acquired about how the technique may address some of the problems already pointed out in this field. HRI studies have difficulties with adapting the robot's behaviour to individual user's needs without running long-term experiments to gather enough user data to train and define the desired adapted robot behaviours.

In this section, the definition of the first set of personas inside the system is presented. In addition, the initial questionnaire that participants need to fill in prior the experiment is depicted. This questionnaire is used to investigate the variables that should be considered to match a user and a persona in our system. Once the association is done, the system will be able to adapt the robot features to the participant's needs and preferences during the first interaction. However, this is the key point to be investigate and just at the end of these research will be answered.

4.2.1 How To Define Personas

As pointed out in the literature (Pruitt & Grudin 2006), the definition of personas should be based on data collected through studies where target users are directly exposed to the final product or the system. The information gathered during a previous study in our research group (Dautenhahn et al. 2005), in addition to some of the information collected during the assessment of the ARS (see Chapter 3) (Duque et al. 2013a), was the starting point to define the first set of personas to incorporate into the initial model investigated. Each of the personas defined characterises a group of end users of the system, in this particular case, people interacting and sharing the same space with a robot companion.

The primary objective after defining the personas will be to associate each one with a particular robot behaviour. This will allow the robot companion behaviour adaptation prior to the first encounter, so that a smooth interaction between users and the robot can be achieved. In order to accomplish that, the current state-of-the-art in the HRI field will be used to define the first version of the computation behaviour model for robot companions. This model will be evaluated and evolved during this research following an iterative methodology as it was pointed in section 1.4. The main difficulties will be to find the association between users and personas by defining the variables able to determine the sort of user who the system will interact with. Also, the initial assumptions taken to define robot behaviours based on personas characteristics must be proven by means of the experiment carried out and described in the following chapters. The outcomes of this research are expected to add to the effort of the HRI community to reduce the burden put on participant for the collection of the necessary data to understand and adapt robot behaviours during the interaction.

As mentioned during the literature review, see Section 2.5, Nielsen's characteristics have been used to guide the definition of the initial set of personas in the system. According to the author, these characteristics will avoid to fall into stereotypes (Nielsen 2008). Also pointed by Cooper during the description of the methodology used to define personas, "Personas should be typical and believable, but not stereotypical" (Cooper et al. 2007). One of the experiment carried out during the COGNIRON project (Dautenhahn et al. 2005) and the recent experiment, *Experiment 1*, performed at the UH Robot House (Duque et al. 2013a), provided enough knowledge to define the first set of personas to use in the initial definition of the model. The COGNIRON experiment involved 28 adults, aged between 20 and 55 years old, and assessed the participants' opinions and preferences when interacting with a robot companion in a simulated home environment. The main findings are summarised below and patterns has been extracted to help define the two initial personas of the system. More recently, a two-sessions trial was performed in the UH Robot House, *Experiment 1*, were potential users of the system provided a good insight about their preferences living in a smart home, the preferred task where a robot could be useful to them and their keenness being assisted by a robot in the future.

For the initial definition of the computational behaviour model, two well differentiated personas were defined. Two 'antagonist' personas, i.e. defining clear differences between their attitudes towards robots, personality traits, and so on, will be a good starting point to initiate this investigation. This approach should show clearer indications about the path to follow in future iterations of the research process. It was considered that a similar definition of the two personas and their robot behaviours associated would create ambiguity during the evaluation process. Meaning, the users could not distinguish between similar robot companions behaviours during the interaction. In my opinion, this is an important consideration to take into account during the creation of future personas. The robot behaviours associated with these personas must depict significant differences with the rest of the behaviours already defined in the system. Also, the definition of personas and the robot behaviours associated are restricted by the hardware limitations and the set of robot features that the selected companion could adopt during the studies.

The main findings has been grouped and summarised in the following bullet points. These will be used to identify the two type of personas that will be initially defined. This results and data have been extracted from one of the COGNIRON deliverables (*COGNIRON: D6.3.1 Evaluation of User Studies on Attribution of Intentionality* n.d.) and used to created the initial set of personas described in the next section, Section 4.2.2.

- Young people felt more comfortable interacting with robot companion than the staff members who normally were older.
- Some correlation were found between the participant's personality characteristics and their perceptions of robot personality.
- Younger participants were less anxious about communicating with robots and more open to having a robot companion compared to older subjects of the sample.
- In general, participants would like the robot companion to be predictable and controllable during the interaction (71%).
- In general, participants would like the robot companion to proactively find out if they need help (37%) against participants that would like the robot to quietly wait until they were instructed to do so (41%).
- Participant would prefer the robot companion to come close (63%) or very close (4%) to them during the interaction.
- The majority of participants indicated that a considerate robot should pay attention (37%) or quite a bit of attention (48.1%) to what they are doing.

- Younger participant preferred a *Socially Interactive Robot Companion* to pay attention to what they are doing compared to older subjects [t(26)=2.07; p=0.05].

According to these results, a distinction between young and older people must be made during the interaction with a robot companions. This will be reflected in the initial set of personas to define. Also, the personas technical knowledge seems to be affecting the interaction with a robot companion. The defined personas must represent a group of users sharing the same goals when interacting with a system. Young people seem to be more open and less anxious about the idea of interacting with a robot, although this effect could be explained by the number hours that younger people could be exposed to technologies during their daily lives compared to older people. In terms of personality, this could play an important role when matching users' personalities and the robot's behaviour according to the results. Therefore, distinct personalities have been defined for each persona based on the main trait pointed in the literature review, i.e. extroversion (Syrdal et al. 2006). Finally, the outcome about predictability and controllability of a robot companion will be considered. A fully autonomous robot taking decisions by itself could be badly rated by users, however, some sort of robot proactiveness must be included in order to enhance the interaction. In the next section, the definitions of the initial two personas of the system are presented based on the data and findings depicted above.

4.2.2 First Set of Personas

Once the bullet points have been defined and the pattern identified, it is possible to proceed to the definition of the personas archetypes (Cooper et al. 2007). Persona must represent a believable character searching for its goal when interacting with a robot companion. Nielsen et al. presented five characteristics to consider for the definition of personas. The first one is the physical description of the persona or the inclusion of a picture **(Body)**. Following the persona overall life style and personality and its influence over technology **(Psyche)**. The persona background must be described highlighting its attitudes and understanding of the world **Background**. The description must point the emotion and feeling of the personas towards technology **(Emotions)**. Finally, personality must be reflected in the definition, either creating a predictable character or a less predictable and engaged one **(Personal Traits)**.

In addition, the three types of user goals defined by Coopper will be considered (Cooper et al. 2007). According to Cooper, the following goals should be depicted in the personas definition, *Experience goals - how someone wants to feel while using a product*, *End goals - user's motivation when performing a task using a specific product* and *Life goals - personal aspirations going beyond the product design.* These goals must be used to defined the robot behaviour thinking about what this personas would like to see and experience when interacting with a robot companion at home. Following these main characteristics and advices by two well-known authors in the personas literature, the description of the two personas were put together with the following result.

4.2.2.1 Jessica


Figure 4.1: Jessica

Jessica [1] is a 22-year-old student at Midwest University in the United Kingdom. She is in her third year of a Mechanical Engineering degree and she has been doing quite well in all subjects so far. She has many friends at University, she is considered a sociable, active and creative person and these qualities make her popular among her friends.

She has a special interest in robots and smart homes. She would really like to have a robot companion at home, and she is thinking about doing her thesis on a related topic. Jessica has the typical university lifestyle, she arrives home at 6 pm from university and she then starts checking her favourite websites and uses social networks to communicate with her friends. She needs to study at least twice a week and solve the exercises of each of her subjects at university. As a future engineer, she is generally interested in technology and she is getting quite excited about the possibility of using a robot at home to help her with some of her daily tasks.

When being asked about what a robot companion means for her and how she will feel living with one, Jessica thinks about robots as a friend, although she does not agree with the idea of robots replacing people. She wants to use the robot for tasks at home, for instance, she is interested in receiving some help transporting objects, checking news or listening to music on the robot's tablet PC. In her opinion, the robot should be pro-active, so if she is cooking, the robot should be aware of this situation and offer help about how to cook the given recipe or just being with her

[1] Image Source: https://www.flickr.com/photos/pburch_tulane/6893162467

during the task. In her opinion, the robot should show the TV guide on its screen when she is watching television or the news of the day when she is lying on the sofa, for instance.

In terms of interaction, she does like the idea of using a robot's tablet to interact with the robot. Nowadays, she is quite used to this kind of touch screen technology and mobile devices interfaces, so she is not worried about how to use it. After several experiences with robots, she feels quite comfortable when being approached by and standing close to a robot companion. The robot's verbal communication could be an extra feature that she would like to have on the robot, but this is not the most important feature for her. Jessica agrees that robots could be a useful tool at home to make her life easier in the future, as well as a fantastic friend. Jessica's main goals using the robot companions could be summarised as follows:

- Enjoying using the robot at home when browsing or listening to some music.
- Using the robot to transport objects from one place to the other.
- Using the robot as a friend or entertainment tool.
- Becoming an expert in the robotics world and helping develop robot companion in the future.

4.2.2.2 Matthew

Figure 4.2: Matthew

Matthew [2] is a 50-year-old bookseller in a small village in the north of England. He and Anna, his wife for 25 years, have been running this business for more than 15 years. They have two daughters and one son, all of them studying in different places around the UK. He is a good friend to his friends, but he is a bit introverted at the same time. He maintains a good relationship with the majority of his customers. He is quite dependable, so his relatives do not think twice about visiting Matthew when they need sensible advice.

Matthew and his wife are considering the option of applying to one of the new pilot research programs carried out by their local council. The participants will have the possibility of having a robot companion at home to help them with the domestic tasks. Nevertheless, they are a little apprehensive about robots as they have never interacted with them before so that they are a bit sceptical about the idea. However, they both think that they will be able to manage the new tool and quickly get used to it, as long as the system is not too complex for their abilities.

His son has been telling them about the benefits of having this companion at home. It could be quite useful on reminders (medicine, appointments and so on), showing their favourite websites or getting warnings about an unusual status of appliances. After a few weeks with the robot at home, they have been trying to get used to this new technology. They have found the robot voice responses and the interface integrated into the tablet PC attached to the robot quite useful. They

[2] Image Source: `https://www.flickr.com/photos/pburch_tulane/6893161493`

like when the robot offers its help to transport objects around the house, especially when preparing a meal or after finishing eating in the living room. The robot moves smoothly around the house and keeps its distance when approaching to them, so they are not afraid of its behaviour, something that makes them more comfortable when interacting with the companion.

Matthew and Anna were a bit worried at the beginning, but as time goes by, they find themselves getting used to the robot and the interaction with such a new technology. Definitely, the robot is helping them make easier some of the daily living activities at home. Matthew's main goals using the robot companions could be summarised as follows:

- Feeling in charge of the robot and capable of commanding and using it on several tasks at home.
- Using the robot to help him during activities of daily living such as preparing food, cleaning the table, laying the table and so on.
- Using the robot as a tool, e.g. medicine reminders or transporting objects to different places around the house.
- Helping to the HRI field to develop robot companions based on the data collected after the experience.

4.2.3 Questionnaire Definition

In order to define the computational behaviour model and evaluate the results after each experiment, the association between the user's characteristics and the robot behaviours shown during the interaction must be found. In the next chapters, different experiments will be performed to try to determine this association, however, an initial questionnaire must be defined in order to depict all the variables to be initially evaluated. There will be later reduced and incorporated to the computational behaviour model depending on the findings. The matching between users and personas will allow the definition of the robot companion features to modify during the interaction to adapt the system to the user's preferences. The most significant variables are represented below and using *italic* format. These variables will be part of the initial questionnaire that participants will fill in before interacting with the robot. The initial questionnaire is a combination of several research studies performed in the field, where these variables resulted interesting and significant during the evaluation of users in similar or related environments. The following six categories were selected to represent all the variables included in our pre-experiments questionnaire.

- *Age, Gender, Educational Level, Technical Background* and *Computer Experience* are defined as influential variables regarding the way in which users interact with technology, and in our particular case, with robot companions (Dautenhahn et al. 2006) (Castro et al. 2008) (Fischer 2001).

- *Previous Experience with Robots, Attitudes Towards Robots* and *Comfort with Robots* are pointed out in the literature as factors that will influence the interaction between the robot and the user. It is known that prolonged relationships with robot companions may influence users' attitudes towards robots (Syrdal et al. 2009).

- *User Personality Traits*, acquired through the Big-Five Personality Test (Digman 1990), are directly related to proxemics and expressiveness features of robot companions. Several studies can be found in the literature about this subject and how the user's personality influences the overall interaction experience with the companion (Williams 1971) (Walters et al. 2005).

- The *Robots' Role* and how users perceive robot companions can be considered influential on different aspects of the robot's behaviour. A recent study was done by Koay et al. has pointed out this finding (Koay et al. 2014).

- *Index of Assistance Level* in ADLs. Robot companions should behave in accordance with the assistance level required by users in each of the activities where the robot could collaborate in the given environment. The index of assistance has been adapted from the one defined by Katz et al. (Katz et al. 1970). We have defined different general tasks where a companion could assist the user in the future, e.g. laying the table, cleaning the table, preparing food, remainder task, and so on. The overall rate on this task will represent the degree in which a user would wish to be assisted before the interaction takes place.

- *Proxemics Preferences* including location, approach direction and facing have been widely studied in the field of HRI, e.g. (Walters et al. 2007) (Walters et al. 2009) (Dautenhahn et al. 2006) (Mumm & Mutlu 2011). These variables are key during the interaction between the robot and the human, and depending on the sort of companion used, they could influence the way in which users interact with the companion after approaching them.

As mentioned above, the combination of these variables has defined the initial questionnaire, see Appendix C.4. This questionnarie will be filled in before any interaction happens between the user and the robot. It will provide the necessary data to identify the types of users that the system will interact with. Once the user is categorised and the model defined, at the end of the investigation, the system will be able to match users and personas to achieved the desired adaptation during the first interaction. In section 4.5, the evaluation methodology to be applied once the model is completely defined has been depicted. Each of the personas will have a robot behaviour associated as part of the specification of the computation behaviour model, therefore the match between the user and the personas will be the tool to adapt robots behaviour to users' preferences during the first interaction. This achievement will reduce the amount of time needed to develop HRI experiment. The collection of data and the analysis of results is an unavoidable task in the HRI field in order to adapt the robot to users preferences. However, and before accomplishing this, it will be necessary to find the variables that determine the user-person match. The experiment to be performed, see next two chapters, will help to answer the research questions proposed for this investigation.

4.3 Robot Features Definition

Once the type of user has been identified through the initial questionnaire, see above, the system should modify the robot behaviour accordingly to adapt its behaviour to the participant during the interaction. A set of general robot's features have been defined to be integrated into the model and be modified during the first encounter with the user, see Table 4.1. Each of the pre-defined personas composing the model will be associated with a robot behaviour as depicted in the initial definition of the computational behaviour in the following section. The set of behaviours to be used are configured prior the interaction in order to make users more comfortable during the first encounter. The main objective during this research will be the identification of the set of variables that determine this association between users and personas, and personas and robot behaviours for smart homes.

In order to create the personas-based model for robot companions as generic as possible, common robot features that could be adopted by the majority of robot companions nowadays were defined, e.g. Sunflower used in LIREC (*LIREC: Living with Robots and Interactive Companions* 2007-2013) or Care-O-Bot 3 used in ACCOMPANY (*ACCOMPANY: Acceptable robotiCs COMPanions for AgeiNg Years* 2011-2014). The main idea behind this is to facilitate the integration of the system described to other HRI researchers who wish to further investigate this approach. The more general the robot companions' features are, the easier it would be to integrate the approach investigated during this research into similar environments. The LIREC project (*LIREC: Living with Robots and Interactive Companions* 2007-2013), which final stage coincided with the beginning of this research, supplied relevant knowledge about the preparation of HRI studies and how to adapt the robot companion characteristics, Sunflower, to better match users preferences during the interaction.

Robot Features Selected
Robot Communication (Tablet and Speech)
Robot Graphical User Interface (Tablet GUI)
Robot Proxemics (Distance and Direction)
Robot Assitance Levels
Robot Expressiveness Levels
Robot Proactiveness Levels

Table 4.1: The robot features to be modified during the interaction

The importance of a good *communication* and a *good interface* to be used during the interaction was already pointed by Bartneck et al. several years ago (Bartneck et al. 2009). There is a need to create something intuitive and adapted to all sort of users by the modification of the interface and the way of interacting with a robot companion. In terms of proxemics, a large research has been done in the area as pointed in Section 2.8.2, the *robot approach* must be considered when interacting with humans and the model already defined should be used in the experiment (Walters et al. 2009). Dautenhahn et al. investigated about the roles that robot should play when interacting with people. The results shown how the robot are thought to help and assist humans at home as much as possible (Dautenhahn et al. 2005). The *robot assistance* level is incorporated based on these outcomes, although different people would require a different type of assistant from robot companions. Regarding the expressiveness, Heerink et al. found how a robot showing a more sociable behaviour was perceived as more enjoyable and sociable during the interaction. The *robot expressiveness* will contribute to enhance the social behaviour expected by users during the first encounter, so this feature must be considered when designing HRI experiment scenarios. Finally, the *robot proactiveness* has been already pointed as beneficial to achieve smoother interactions. Satake et al. used a proactive robot to initiate conversations between a robot and a customer in a shopping mall. The results shown how the proactive robot was a useful mechanism to catch people attention and initiate the conversation (Satake et al. 2009). Different levels of proactiveness should match different group of participants during the HRI experiments.

These initial set of features selected will be evolved as part of the iterative process followed during this research, as it was previously described in this document.

Following an extended version of the robot's features depicted in the Table 4.1 are explained.

- Robot Communication
  - Tablet Touch Screen - The user and the robot will interact through the tablet touch screen installed in the front part of the robot. This screen will be available at any time during the interaction with the robot companion.
  - Verbal Communication - The robot has the capacity of communicating the system status by voice commands and this will be used in conjunction with the touch screen to enhance the interaction.
- Robot Graphical User Interface
  - Font Size - Users may require a bigger font size in the interface in order to ease the interaction with the robot's touch screen.
  - Interface Feedback - The system will inform the user about each task completed. Inexperienced users will need to know the system status more frequently than experienced users.
  - Simple Interface - This option will activate a simplified version of the interface. Inexperienced users could benefit from the interaction with the robot when this option is activated.
  - User Error Prevention - The system has to prevent input data errors. The generation of a clear and simple interface will allow us to achieve this purpose.
- Robot Proxemics

  - Approach Distance (Personal or Social Zone) - The robot companion will stand in front of the user maintaining a personal or social distance between them.
  - Approach Direction (Front Left, Front or Front Right) - The robot will approach the user following one of the possible direction mentioned.
  - Facing - The robot will turn its head towards the user's position in order to enhance the interaction.

- Robot Assistance - The robot will offer its help during users' activities at home. The frequency of that will depend on the user's needs. We will consider two level of assistance in the robot companion, *High* and *Low*.

- Robot Expressiveness - The robot will show a different level of expressiveness depending on the user's personality. Two levels of expressiveness, *High* and *Low*, have been considered just as stated on the assistance level explanation.

- Robot Proactiveness - The robot will make its own decisions based on the status of the system. The level of proactiveness will depend on the user's characteristics. Two levels of proactiveness have been considered just as stated on the assistance level explanation.

In the following chapters, further information will be provided about the different levels of interaction specified for each robot feature presented and how this will be modified and shown during the experiment (see section 5.4 and section 6.4). Initially just two levels, *Low* and *High*, will be considered for each of the robot features specified in order to facilitate the recognition of the distinct behaviours by participants.

All these features can be found in the robot companion to be used during this investigation. Sunflower (Figure 4.3) was the robot selected to perform the entire research described in this dissertation. Sunflower is a mechanoid robot developed by Dr Kheng Lee Koay as part of the LIREC project. It is based on the Pioneer platform (Adept MobileRobots) with the addition of a head with 3-DoF, a touch-screen user interface, and diffuse LED display panels situated over the torso to provide expressive multicoloured light signals to the user. The robot has been successfully used during the LIREC project and later studies performed at UH Robot House, e.g. (Koay et al. 2013) (Salem et al. 2015) (Koay et al. 2016) (Chanseau et al. 2016). The amount of research done with this robot in similar experiment will allow to focus in the main point of this research without using large amount of time evaluating each of the behaviours that this robot can show during HRI experiments. There is enough research and findings to support the friendly view that participants have about it when first interacting.

4.3.1 The Behavioural Model - Initial Definition

Once the personas and the robot features are defined it is possible to specified the initial association between robot behaviours and personas during the interaction. This is the first approach to the model which will help defining the scenarios of the *Experiment 2*. The experiment's outcomes will be used to re-adjust this initial definition and expand the first set of personas and the robot featured created as part of an iterative process. The first definition of the model can be found in the Table 4.2. This first model tries to reflect the definition of two well differentiated personas with different needs and preferences when interacting with a robot companion. The robot features will be just modified in two different ways in order to facilitate the definition of the model and design of behaviour during the interaction. As pointed out before, it was quite important to implement robot behaviours that could be distinguished by the participants. Users' robot experience could be from none to expert, so users with none experience interacting with a robot companion will find difficult to discern the differences between two robot behaviours whether these are close to each other. This issue must be always considered during the definition of HRI experiments in order to avoid unexpected results due to misinterpretation of the system.

The first persona has been defined as a young person, extrovert, used to technologies and keen on the idea of interacting with a robot. The persona main tasks

Figure 4.3: Sunflower Robot Companion. Picture taken at the UH Robot House by the author of this dissertation.

are to use the robot as entertainment, assisting to some home tasks and learning from the robots to become an expert in the future. Based on this definition, and the outcomes pointed out from the COGNIRON experiment (Dautenhahn et al. 2005). Jessica, the first persona, is expected to prefer a more complex interface in the robot, a robot approaching closer to her, a robot assisting just when necessary, a robot quite expressive and a robot making decisions by itself.

Robot Feature	**Conditions**	**Jessica**	**Matthew**
Communication	Advance Interface	X	
	Simple Interface		X
	Robot's Voice	X	X
Proxemics	Personal Zone	X	
	Social Zone		X
Assistance Level	High		X
	Low	X	
Expressiveness	High	X	
	Low		X
Proactiveness	High	X	
	Low		X

Table 4.2: Initial Definition of the Behavioural Model - Two well differentiated personas and robot behaviours associated

Regarding, the second persona, it has been defined as an adult, a bit introvert and dependable person, apprehensive about robots but exciting about the possibility of having one at home. The persona main objective is to have a service robot at home able to help with the daily. The robot should be highly predictable and easy to use. At the same time, the persona will like to help the HRI community to learn from this experience and further develop in the future. Based on this definition, Matthew, the second persona defined, is expected to prefer a simple interface, a robot keeping a fair distance during the interaction, a robot assisting him as much as possible during the home tasks, a polite and not quite expressive robot and a predictable robot not making too many decisions by itself.

These assumptions and the first definition of the is depicted in the Table 4.2 which collect all the thoughts presented at the previous lines. This initial definition will be investigated and evolved based on the outcomes from the *Experiment 2* and *Experiment 3* which will be presented in the following chapters.

4.4 Architecture and System Definition

The computational behaviour model investigated will be integrated into the current UH Robot House system in the future. A general architecture to connect all components must be designed in order to be able to expand and modify those based on the outcomes achieved at any time during the iterative research methodology being followed. The main focus is to create a system to modify robot companions' behaviour in order to behave in a social way when interacting with users in the home environment. Creating an architecture that works well in different environments is still an open challenge in the HRI field.

A whole set of cognitive architecture has been presented over the years in the field. For instance, ADAPT tried to develop a whole range of cognitive abilities based on SOAR (Benjamin et al. 2004). An embodied version of ACT-R, ACT-R/E, was used on robots to coordinate tasks between a human and a robot as part of a team (Trafton et al. 2013). CiceRobot is another example of cognitive architecture exploring the way to react to the environment based on the use of expectation in the perception loop (Chella & Macaluso 2009). A newer version of SOAR was developed in conjunction with vision and motor-action to interpret object in the environment where used (Laird 2012). Similarly, but based on the connection of ACT-R with a neural implementation of a visual system, we found SAL (Synthesis of ACT-R and Leabra) which is used to distinguish between object for recognition tasks (Vinokurov et al. 2012). In general terms, these approaches have been able to achieve their goals but limited to the tasks for which they were designed. As pointed by Chella et al., none of them has inspired the community to move away from the typical coded robot behaviour to a generative architectural view (Chella et al. 2013). Therefore, it is important that researchers keep investigating the way of closing the gap to incorporate more intelligent responses into robots in the near future.

In this research, a modular architecture is defined and its benefits and disadvantages, will be described across this dissertation and shared with the HRI community while investigating a novel approach to adapt robot companions behaviour before the first first encounter. This architecture cannot be compared to the cognitive architecture presented above, instead the main focus was to created a modular and general one inspired by current research in the field but at the same time adapted to the system already defined into the UH Robot House. Another important aspect taken into account when developing the system was the migration from one robot companion to another. For instance, Sunflower was the robot companion used during the entire investigation, however, the system was kept compatible with a different robot companion which could be used in future work, Care-O-Bot 3. This will give the possibility to further investigate this approach in a different robot platform. In this section, the system architecture is presented. This has been considered the most suitable to achieve the research target and successfully integrate the personas-based computational behaviour model into the current system while keeping the compatibility with the ACCOMPANY project.

The first decision made about the architecture was to base the entire system on a centralised database. The benefits of this approach are numerous: reliability, efficiency and scalability when dealing with a large amount of data and subsystems (Derbinsky et al. 2013). The ACCOMPANY European project adopted the same centralised architecture which will make the integration easier between systems and the use of a different companion in future work related to this research (Saunders et al. 2016). The ACCOMPANY project architecture is depicted in Figure 4.4. Given the similarity with our approach, we decided to integrate the human activity

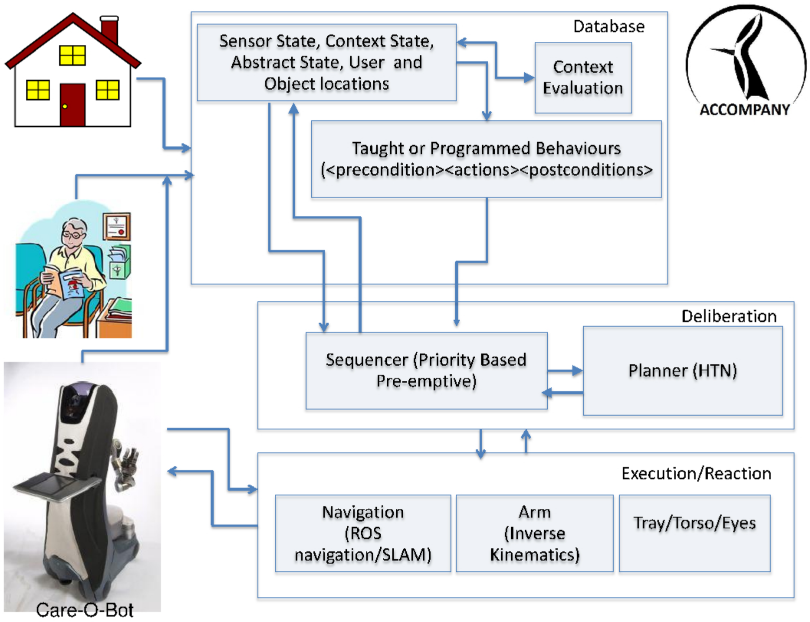

Figure 4.4: Accompany European project architecture definition. *Obtained from the contribution (Saunders et al. 2016) and included with the permission of the authors.*

recognition system (Duque et al. 2013a), and the personas specific modules into the same database so the European project, so this was able to make use of both of them in the future. In addition, and as mentioned above, the robot connector interface will give the possibility to use the system independently of the robot platform adopted. This approach adds value to this research since the use of a different companion, in future work of this research, was always taken into consideration during the design stages of the system presented. In order to clarify the architecture adopted, the most representatives modules, their features and their internal operation are explained below. A representation of the system architecture can be found in Figure 4.5. The main modules defined in the system architecture are as follows:

- *Pesonas Module* - This module will be responsible for matching the user to the pre-defined personas of our system. Each participant will be asked to fill

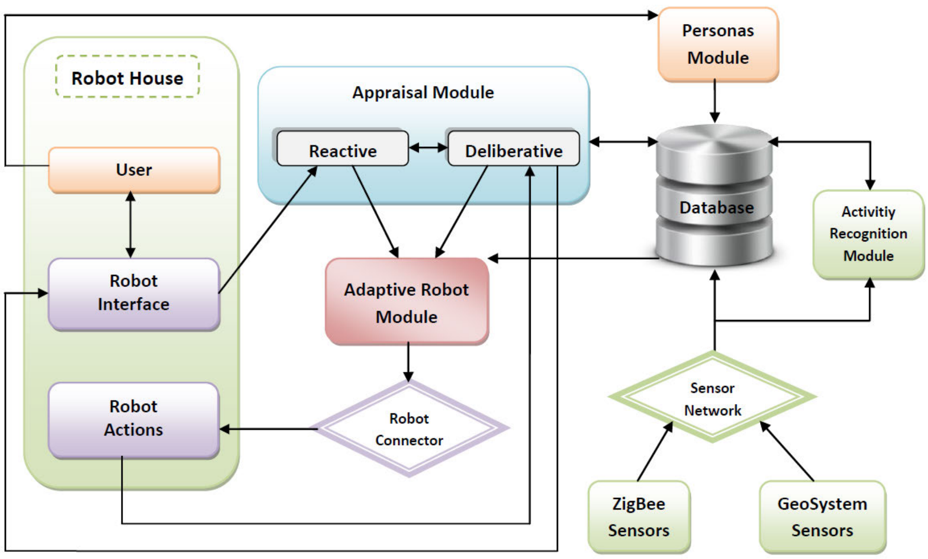

Figure 4.5: Architecture and Modules in our system definition - To be integrated alongside with the Accompany architecture

in an interactive questionnaire through which the comparison and matching will be calculated. The result will be stored in the database, in addition to the user's preferences selected through the questionnaire, for instance, news, recipes, music or weather favourites websites, so these can be displayed on the tablet PC attached to the robot companion during the interaction. At the end of the research, this module should define the set of user variables that were found significant for the comparison to the pre-defined personas. These variables will be determined by the outcomes found during the investigation.

- *Apprasial Modules* - Following the approach used in the Fatima model (Dias & Paiva 2005) and similarly introduced by the ACCOMPANY project on its architecture definition (Saunders et al. 2013b), the terms of *Reactive Appraisal* and *Deliberative Appraisal* have been adopted for the definition of the system. The reactive part will be the one responsible for the evaluation and performance of the commands sent by the user directly to the robot, i.e. those that have no need to be processed or consider the system's status. On the other hand, the deliberative component will make decisions based on the context for each different situation and the user's preferences that were stored by the *Personas module* when the user filled in the initial questionnaire. The Sequencer module, developed during the ACCOMPANY Project, will be used to define the actions that the robot must execute in each situation depending on the context and the user's preferences (Saunders et al. 2016).

- *Adaptive Robot Module* - Based on the data stored by the personas module in the database, this module will be responsible for adapting the robot's behaviour according to the type of users and their characteristics identified by the system. Before the system sends the instructions to the *Robot Connector*, the module checks on the database which persona is selected *Personas Module*, and which parameters have to be applied to adapt the robot's behaviour accordingly. Then, the adapted command is sent to the companion and the system gets updated once the companion finishes the action.

- *Robot Connector* - This component will be responsible for adapting and sending the command to the selected robot companion. The connector can be defined as an intermediate layer that abstracts the low-level hardware component from the higher level layer defined in the system. This intermediate layer will send and receive commands independently of the robot selected to interact with the system. This methodology allows for switching companions without altering any features of the current system, the only component that needs to be created will be the specific intermediate communication layers for the robot companion being used. These sorts of mechanism make the system more versatile when thinking about future changes of the robot to be used.

Based on the main modules described above, the architecture presented will be tested and proved as a suitable one towards the creation of a generic, expandable and easily upgradable system to integrate and develop the personas-based computational behaviour model. Other applications have been developed along with the main modules aforementioned. For instance, a new GUI (Graphical User Interface) has been defined to establish the communication between the user and the companion during the interaction which can be adapted in terms of font size or the sorts of menus to be displayed depending on the user's requirements. An example of the interface developed can be found in Figure 4.6:

In order to integrate the system into the centralised database defined, several data tables were introduced and others expanded in order to adapt the current UH

Robot House system to this system and allow future features to be incorporated. The ARS presented in Chapter 3 was adapted in order to retrieve all the activities recorded and stored in the database. The incorporation of the activity recognizer into the current architecture of the system was done by adding the data and the tables that the ARS was requiring into the centralised database. This data includes each sensor's details and status, the sorts of activities recognised and status, the user's preferences and personas defined into the system. The main modifications carried out to integrate the ARS system into the database and fully adapt all systems are as follows:

- *Users* table. New column created in the existing table to represent the persona associated with the user during the experimental procedure.

- *UserPreferences* table. A newly created table that contains the user's prefer-

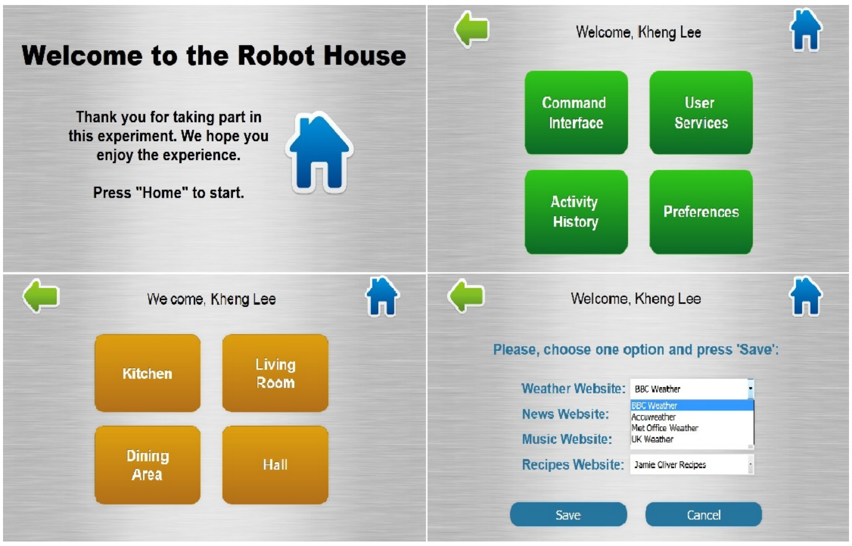

Figure 4.6: Interface deployed into the robot companion's tablet PC. Used by users to communicate with the robot during the interaction.

ences regarding the graphical interface and a few features of the companion to be adapted during the interaction.

- *Personas* table. A newly created table to define personas and the features associated to these personas. This will determine the way that the robot will behave during the interaction with the user.

- *Activites* table. A newly created table containing a short description of the activity and the current status, including when the activity was last time activated and deactivated.

- *Sensors* table. New sensors details and their current status as required by the ARS were incorporated into the existing sensors table.

More details about the MySQL tables, source code and scripts created can be found in the following GitHub repository (*Thesis Database Files - GitHub* 2016). Using this platform to provide the source code avoids the need to include long sections of code into the appendix of this dissertation, and at the same time, makes this information more accessible to other researchers. Nevertheless, this extra information is not affecting the understanding of this research and it is completely optional for the reader. The main author repository where the code has been upload can be found in the following link (*Thesis Software Modules - GitHub* 2016). In the Chapter 7, the performance of the architecture performed during the research process will be discussed, and whether the purpose for which it was created was fulfilled. Therefore, the *RQ1* will be answered and the advantages and the disadvantages of using it will be described on that chapter.

4.5 Methodology and Evaluation

As introduced in section 1.4, an iterative methodology (Arkin 1998) (Larman 2004) has been considered to be the most suitable to carry out this personas investigation. This methodology allows to better understand the challenges to integrate the personas technique into the HRI computation behaviour model, and define step by step the variables to be considered in order to modify the way in which the robot companion should behave to suit user preferences during the interaction. As a direct consequence, and based on the findings, the first set of personas defined into the system will be modified and each iteration will guide the direction to be followed. The findings will determine the feasibility and challenges of using the personas technique in the HRI field as means to introduce social skills and adapted behaviours into robots. The success of the integration of this HCI technique into the HRI field is expected to increase the acceptance of robot companions by humans during the first interaction. The final findings will be discussed at the conclusion of this research.

All the studies will be performed in the UH Robot House, a naturalistic environment used by our department to perform studies between humans and robot companions, see Figure 3.1. This is a fully sensorized environment but otherwise a standard British semi-detached house. The companions currently held in the UH Robot House came from a combination of several research projects over the years (*COGNIRON: The Cognitive Robot Companion* 2004-2007) (*LIREC: Living with Robots and Interactive Companions* 2007-2013) (*ACCOMPANY: Acceptable robotiCs COMPanions for AgeiNg Years* 2011-2014). The main target has always been to introduce social skills into the robots so users feel more comfortable during the interaction at the time that we study a particular topic within the HRI field in smart homes. All resources available at the UH Robot House, including the Sunflower robot companion, were used to carry out this research. These include computers and other network devices installed across the experimental area that were necessary to run the entire system. As described in Chapter 3, an ARS was developed and integrated into the previous network system in order to expand its functionality and enhance the general interaction capabilities showed by the companions during the experimental sessions.

A broader description of the two different experiments, *Experiment 2* and *Experiment 3*, that will be carried out at the UH Robot House are addressed in the upcoming chapters. However, the *Experiment 2* objective was to find out the user's preferences when interacting with a robot companion at home. This will help to identify the relation between user variables and robot behaviours in order to de-

Figure 4.7: Inside the UH Robot House. Source: `http://adapsys.cs.herts.ac.uk/images/gallery/picture_gallery/robothouse-1.jpg`

fine the computational behaviour model upon the results of this study. In order to achieve this, participants evaluated all different behaviours that the robot companions could adopt during selected tasks of daily living at the UH Robot House. Each of the behaviours is associated to one of the personas defined in the initial model. After the evaluation, it will be possible to identify which behaviours were preferred by which users and the variables that could better represent this association with personas. In the *Experiment 3*, the participants needed to collaborate with the robot companion to complete a set of daily living tasks defined in the scenario described. The main objective was to evaluate the set of personas defined in the system and the behaviours associated with the robot during the execution of the tasks. Each individual performed, in a random order, the same scenario three times, one per persona, and each time the robot features were modified to match the behaviour associated with each persona based on the model specifications. After the interaction, the users were able to evaluate how comfortable they felt during the interaction based on the robot behaviour shown. Both experiments will be explained in the next two chapters of this document.

Regarding the computational behaviour model, the questionnaire created in section 4.2.1 will be used to match users and the pre-defined personas in our system in order to apply the most suitable behaviour into the robot companion during the first encounter. As aforementioned, this questionnaire will provide a better insight of the types of users that the robot will interact with. The main challenge will be to define the significant variables to match each individual with one of the pre-defined personas so that the model determines the robot's behaviour to be adopted for the specific user currently interacting with the system. This questionnaire will be evaluated and modified after each iteration following the methodology proposed, so that the latest version of the model will contain all the knowledge collected during the investigation.

Therefore, a way to calculate the similarities between users' answers and each persona's pre-defined values will be needed once the significant variables from the initial questionnaire are identified, see section 4.2.3. Each of these pre-defined personas' values will be calculated from the mean values of participants preferring the same robot behaviours during the final study of this dissertation. The final similarity values should be calculated as an average of correlations values for each subgroup of variables identified as significant. This subgroup will be determined by the six categories defined for the initial questionnaire, see section 4.2.3. Several similarity measures than can be found in the literature, e.g. (Breese et al. 1998) (Vozalis & Margaritis 2003), however, I would suggest one of the most common, the Pearson Correlation coefficient r (Pearson 1895). This coefficient measures the linear correlation between two quantitative variables X and Y. The result value is set to the interval [-1,1], being 1 total positive correlation, -1 total negative correlation and 0 no correlation between the variables. The formula for the Pearson Correlation coefficient r is:

$$\rho(X,Y) = \frac{\mathbf{Cov}(X,Y)}{\sqrt{\mathbf{Var}(X)\mathbf{Var}(Y)}}.$$

As presented in the previous section 4.2.3, a set of different categories were defining in the initial questionnaire to evaluate different aspect of users. The correlation between the user's characteristics and the characteristics defined for each of the personas integrated in the model, once these are specified based on the research findings, will be calculated for each category. After the correlation for each category has been calculated, the average of all correlations can be calculated using the *Fisher z-transformation* (Corey et al. 1998). Given a sample correlation r the z value is defined as:

$$z = \tanh^{-1}(r) = \frac{1}{2}\ln(\frac{1+r}{1-r}).$$

After the z values for each r correlation coefficient is averaged we can convert that value back to an r value. The inverse of the *Fisher z-transformation* is formulated as follows:

$$r = \tanh(z) = \frac{\exp(2z)-1}{\exp(2z)+1}.$$

This is the suggested evaluation methodology to determine the sort of participants interacting with the system and select the matching persona from the system, and therefore, its robot behaviour associated to be applied during the first encounter. This functionality will be integrated inside the Personas module, one of the components of the architecture depicted in section 4.4. Once the computational behaviour model is investigated and defined, it will be possible to identify the type of users through the data provided in the initial questionnaire. In this way, the robot behaviours can be modified before the interaction with the user. The definition of the model is the main target and this will be based on the outcomes obtained during each iteration of the investigation as described in the following chapters.

4.6 Discussion and Conclusion

In this chapter, several key components have been defined based on data and initial assumptions to be tested during this research as part of the iterative methodology used. The first set of personas has been defined through the data supplied by previous experiment done in our research group. The initial questionnaire to determine the type of user interacting with the robot has been created based on the literature review investigated in the area. The set of robot features has been selected as general as possible to allow the integration of this approach into similar environment that could be found in other research centres. Also, the architecture defined has been presented and the reasons that makes it suitable have been exposed in previous sections. Finally, the methodology to use during the research has been explained, as well as the suggested evaluation process to apply in order to match users and personas once the variables forming the model has been defined at the end of this investigation.

Once the initial configuration of the system has been defined, it is possible to start evaluating this approach through a set of HRI experiments. The following chapters will described all the steps follow to perform these experiments and the outcomes achieves. Each of the experiments, *Experiment 2* and *Experiment 3*, will be used to define the next version of the model learning from the positive and negative outcomes obtained during the evaluation process. In this way, it can be assured that the iterative methodology adopted will be used to improve the initial version of the model and system defined in this chapter. There are some limitation in the way of evaluating the system, which will be pointed in the last chapter, see Section 7.4. However, in the field of HRI the collection of user data is limited and there is a need for making certain assumptions based on previous research in order to open new ways of investigations in the field. Any of the decision taken during the research process will be explained in order for any other researcher to replicate the steps followed and avoid facing the difficulties that could be described in this dissertation.

Chapter 5

Evaluating Personas in Human-Robot Interaction Studies - First Iteration

5.1 Introduction

This chapter presents the definition, evaluation and analysis of the *Experiment 2* performed during this research. The UH Robot House was also used to run this experiment, as occurred in the previous *Experiment 1*, see Chapter 3. However, this will be the first time that the persona-based computational behaviour model approach will be evaluated and the participants will interact with the robot companion, Sunflower (see section 4.5). The following lines describe the purpose of this experiment, the design process and the outcomes obtained after running the study with 20 participants. The research questions RQ2 and RQ3 are investigated during this chapter and in the conclusion our findings are described in relation to these questions. The *Experiment 2* was performed under Ethics Approval protocol number a1213-13.

In the previous chapter, see Chapter 4, the system architecture developed and the initial behaviour model, including the first set of personas, were presented. Taking into account the initial assumptions made, the experiment was designed to present the distinct robot features to a group of 20 participants for their evaluation. The analysis of results in this experiment will provide the data to define the match between users and the personas created in the system. This association will enable the definition of the computational behaviour model targeted, so that initial social skills can be incorporated into the robot companion without involving users from early stages of the development process. This will help to close the gap between the development of social interactive systems, where robot companions are included, and the adaptation of those to humans when first interacting.

This chapter is organised as follows. Section 5.2 describes the main purpose of the study and expectations. In section 5.3, the research questions are presented and how they are addressed during this experiment, in addition to several sub-questions associated to each of the main research questions. Section 5.4 presents the system description where the experiment took place and the robot companion used. The next section, Section 5.5, describes the experiment, including participants and the conditions which they were exposed to during the evaluation of the system. In section 5.6 the main findings are described based on the analysis of data carried out over the data collected. Finally, section 5.7 discusses how the outcomes of the *Experiment 2* are going to be used for the next iteration of the system and presents the conclusion after performing the experiment described in this chapter.

5.2 Purpose of the Study

The main purpose of this study is to find out users' preferences when interacting with a robot companion, in addition to gather more information about their personalities and needs at home. All the information collected will be used to evaluate how the initial set of variables, defined in the initial questionnaire (see section 4.2.3), could be used to match users to the pre-defined personas of the system. The first set of personas and their characteristics guided the definition of the robots' behaviours shown on each of the robot features that the users evaluated during the experiment 4.3.

As aforementioned, this study was carried out at the UH Robot House, where the participants performed a set of tasks to measure their preferences when interacting with the robot companion. After each task, the participants were asked to rate their level of comfort during the interaction based on their preferences and personal experience. The sessions were video recorded in order to support the data collection, in addition to the demographic user data such as age, background or personality traits being gathered at the beginning of the experiment using the initial questionnaire presented at section 4.2.3. This information was later used to analyse the data and find correlations between the user's characteristics and the robot behaviours shown in each particular task performed at the UH Robot House. Based on the experimental outcomes, a redefinition of the initial set of personas was addressed, as well as modifications of the robot's features to be shown during the next iteration of the system.

The final target is to determine how users and personas could be matched by defining the user variables that identify the type of participants preferring a certain robot behaviour over others. The achievement of this task allows the definition of the computational behaviour model so that the system could be adjusted to suit the user's expectations and needs when first interacting with a robot companion. Therefore, the first step is to determine which robot behaviours and features are preferred by which type of users, so user's characteristics to personas can be associated in later stages of this research. This approach will focus on investigating ways of creating a smooth and socially accepted interaction during the first encounter. The collection of extensive user data prior to the interaction between the user and the robot should be avoided . This novel approach investigate the possibility of achieving this in the near future.

5.3 Research Questions

As mentioned before, the problems surrounding HRI studies are well-known in the literature. The difficulties in searching participants and asking them to repeatedly perform trials inspired the investigation of a different approach to tackle this problem. The creation of a computational behaviour model on the basis of the persona technique could help reduce the impact of some of the current problem pointed out in the field. The reduction in the number of trials to be carried out during early stages of the research process would be one of the main advantages of defining such a model. To the best of my knowledge, only a few HRI studies have introduced this technique into the field, but none of them took the same approach of using persona as the core component to design and modify robot companions' behaviours in home environments. In these environments, the robot behaviours and its adaptation to the user's needs is a vital feature to incorporate in order to increase the system acceptance by humans.

This experiment should provide a valuable insight into the difficulties, and possibilities of achieving the personas-based computational behaviour model for robot companions. This research is responsible for creating, evaluating and learning which variables could be used to match the real users of the system to one of the personas defined. An initial set of person was created and these were used to guide the definition of the initial model and how the robot behaviour should be modified to fulfil each persona requirements when interacting with a robot. Following an iterative methodology, this initial definition will be evolved and adapted after investigating and analysing the data collected during this experiment. The following are the research questions, and sub-questions, that will be addressed during this chapter:

RQ2: *Would people with similar background, characteristics and personality prefer the same robot behaviours and responses during the interaction?*

1. Does the first set of personas represent the category of users interacting with a companion?
2. Does the initial behaviour model definition need to be modified or expanded based on the experiment outcomes?

RQ3: *Which are the most significant variables found that could help identifying the users' preferences and needs so we are able to adapt the system appropriately?*

1. Have the different robot behaviours presented been identified by the users during the evaluation process?
2. Have previous frameworks defined inside HRI got similar results when investigating the variables individually?

Hypothesis: Based on the previous research questions, the following results could be hypothesised after running the experiment and analysing the data collected:

1. H1 - Users with similar personality traits would rate certain robot behaviours similarly.
2. H2 - The initial set of personas will need to be expanded in order to represent the different user groups interacting with the system.

5.4 System Overview

A study taking into account the initial definition of personas (see section 4.2.2) and the behaviour model (see section 4.3.1) was conducted at the UH Robot House based on the system and architecture presented in section 4.4. The sensor network and the activity recognition system, see Chapter 3, were running during the experiment in order to add contextual information to the tasks performed by the users. The ARS was responsible for updating the database with the user's activities detected during each of the scenarios described in the following section 5.5.3. After the contextual information was updated, the *Sequencer* module checked that all conditions were met before triggering the robot action defined on each individual scenario (Saunders et al. 2016).

The participant's demographic information, personality and robot interaction preferences were gathered before the experiment through a closed format questionnaire, see section 4.2.3. During the study the users rated the robot behaviours according to their preferences and, at the end, a post-questionnaire was conducted to gather further information about the users' lifestyle. These questionnaires have been included as Appendix C for further information. The experiment was partly video recorded in order to create samples of interaction between the participants and the robots when performing a collaborative task at the UH Robot House (See Figure 5.1). All the data collected will be used to investigate the most influential variables that make a robot behaviour be preferred over others during the interaction.

Figure 5.1: Scenarios examples with Sunflower in the UH Robot House. Assistance scenario (left) and Proactiveness scenario (right)

Sunflower, presented in the previous chapter, see Fig. 4.3, is the robot selected to perform the experiment. Two conditions, *Low* and *High*, are specified for each of the robot features defined in section 4.3. For users having no experience with robots, it could be difficult to differentiate robot behaviours close to each other. This was the main reason to create just two conditions per feature studied. The main experiment's target is to evaluate each of the conditions with all participants in order to understand their preferences when interacting with the robot. This will help define the links between a certain type of user and their preferred robot behaviours.

In order to achieve this, the participants individually rated their comfort level with each of the two conditions presented for each of the robot features evaluated. The following scenarios were defined in order to present the two conditions per robot feature to all participants. The definition of personas, see section 4.2.2, guided the specification of the behaviours defined in an attempt to adapt them to each particular persona. As Cooper mentioned, personas should be created as believable character able to transmit emotions and feeling to the developers (Cooper et al. 2007). Any other researcher trying to replicate this experiment should adapt the robot features selected to the particular robot capabilities. It cannot be expected to thoroughly replicate what it is described in theses lines, but to follow the methodology used during this investigation to achieve the same goal.

- Robot Communication
  - Low Condition (Simple Interface) - The interface will not give access to modify certain preferences thus reducing the number of menus the user could navigate through. This mode is meant to facilitate the interaction and avoid the user thinking about preferences to be adjusted during the experiment.
  - High Condition (Advance Interface) - The interface will include several menus where the user could modify their selection over the preferences chosen during the initial questionnaire. This option will give the users a better control of the system whether they decide to change some preference during the interaction.
  - Verbal Communication - This is an independent condition available inside

the communication features defined for the robot. The robot will be able to communicate the messages through its speaker. The activation or deactivation of this feature will be optional, and all messages will still be displayed in the tablet PC at any time.

- Robot Approach Distance
  - Low Condition (Social Zone) - The robot companion will keep a distance greater than 100 cms when stopping in front of the user.
  - High Condition (Personal Zone) - The robot companion will keep a approach distance of 50 cms approximately when stopping in front of the user.
- Robot Expressiveness Level
  - Low Condition - The robot companion will reduce its expressiveness level by avoiding flashing its torso lights when interacting with users.
  - High Condition - The robot companion will use the flashing light on top of its torso to catch the user' attention during the interaction.
- Robot Assistance Level
  - Low Condition - The robot companion will not proactively offer its help to transport an object from one location to another, instead the robot will show an empathy behaviour and will go toward the area where the user is located in case some assistance is needed.
  - High Condition - The robot companion will proactively offer to transport an object for the user from one location to the other.

- Robot Proactiveness
  - Low Condition - The robot companion will ask the user for confirmation before executing a task. Based on the current status of the system the robot could determine the action to execute next but without user's confirmation, this will not be executed.
  - High Condition - The robot will make its own decisions based on the status of the system. Depending on the task the user will not need to confirm the action and the robot will execute the task after advising the user about its next movement.

5.5 Experiment

5.5.1 Experiment Setup

The UH Robot House was the naturalistic environment used to perform the *Experiment 2* that should help understand users' preferences when interacting with robot companions. At the beginning, the house and the robot features were presented to all users during an introductory session to make them comfortable with the environment (see Fig. 5.2). Users were advised that their participation in the study was entirely voluntary. They were allowed to withdraw the experiment at any point during its execution. In addition, they were informed that the questionnaires provided did not have any right or wrong answers, nor should they be viewed as tests, and they had the freedom to avoid answering any question whether they felt uncomfortable about it. Just one session per user was required for this experiment and it took approximately one hour to be completed.

In the previous experiment, *Experiment 1*, it was possible to understand how

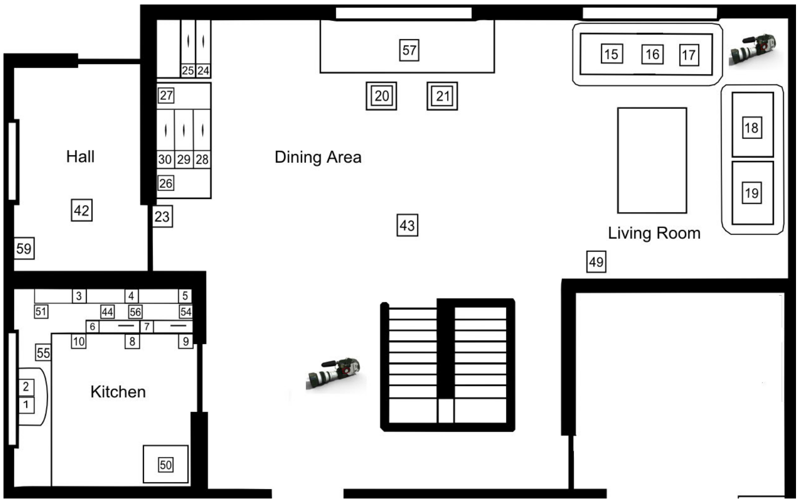

Figure 5.2: UH Robot House map representing the experimental area, ARS's sensors location and cameras position.

users behave in a domestic environment in order to develop a system to make robots aware of the context when interacting with humans. In this new experiment, the users' preferences and needs when interacting with a robot at home are the main features to be evaluated. The users were asked to behave as they were in their own houses as they were not being evaluated. This research involved a few questionnaires, the collection of video or audio material as required and a post-experiment interview to gather some extra information about the users' lifestyle. Participants were informed that all data collected will be treated with full confidentiality and the *UserID* code formed the basis of the evaluations process, not their real name.

After the consent form was signed, the introduction to the experiment was given, see appendix C.3, and the users filled in the pre-experiment questionnaire using a laptop computer, see appendix C.4. This questionnaire was integrated into the *Personas Module* (see section 4.4) in order to facilitate the data collection and later analysis. Once the questionnaire was completed, they were asked to perform a set of scenarios which included two conditions per scenario. The robot companion performed just one condition at a time, see section 5.5.3 below. Immediately after each condition, users marked their preferences in a simple 5-points rating scale defined in the questionnaire (see Appendix C.5). All the conditions were individually evaluated, and randomly presented to the users, *Counterbalancing*, in order to avoid the order effect issue from repeated measures studies. At the end of the session, and after evaluating all the conditions, users completed the post-experiment interview to collect further information about their habits at home and lifestyle. Those data could supply an extra source of information when the rating data is not able to explain some behaviours.

5.5.2 Participants

A total of 20 participants (7 female and 13 male) took part in the *Experiment 2* carried out at UH Robot House. The participants were led by the main researcher during the duration of the whole experiment and a briefing about the house facilities and robot companion capabilities was given before starting the experiment. The participants were asked to perform as if they were in their own house during the experiment, trying to make them feel as comfortable as possible. They were allowed to use any of the resources located at the UH Robot House experimental area, so no particular restrictions were made. The demographic data is summarised in the following table (see Table 5.1):

All participants were recruited from the local area and the University of Hertfordshire. It was no particular interest to investigat any gender or age-related differences when interacting with companions, so this sample is a mixture of ages, genders and technical backgrounds without following any particular pattern. As the majority of

Variables	Value	N(20)	Percentage
Gender	Male	13	65%
	Female	7	35%
Age	Under 30	12	60%
	30-45	8	40%
Background	Technology Related	14	70%
	Non Technology Related	6	30%
Previous Experience with Robots	None	9	45%
	Rarely	5	25%
	Occasionally	6	30%
	Expert	0	0%
Number Hours Using Computer/Technology	Less or equals to 8 hrs	8	40%
	More than 8 hrs	12	60%

Table 5.1: Summary table - Demographic data from our sample (N=20) in the *Experiment 2.*

the participants were no older than 30 years old, it can be assumed that they are exposed to technologies on a daily basis (e.g. using the computer at work or another kind of portable devices as tablets or smartphones). This has been the reason to divide the *Number of Hours Using the Computer/Technology per Day* category into two different values, less or equal to eight hours or more than eight hours, as depicted in the previous table.

5.5.3 Robot Behaviours and Scenarios

A set of robot scenarios were defined in order to individually present each of the robot features implemented. Each scenario was divided into two sections, corresponding to the two well differentiated conditions that were evaluated per robot feature. These scenarios were presented after an introductory session where users got familiarised to the environment and the robot. The different scenarios created per robot feature, and the specific way in which the robot behaved during the interaction, are presented below.

5.5.3.1 Robot Communication

Two interfaces are shown and described to the participant in the same way during the experiment. As part of the scenario, users are asked about their preferences regarding the robot's voice, so they can choose between the robot speaking all messages loud or not through the inbuilt speaker. The two interfaces, *Low* and *High* Condition (see section 5.4), are presented to users for evaluation. The rest of the robot's features remained the same for both conditions.

5.5.3.2 Robot Approach Distance

The participants stands up in the dining area place, and the robot approaches them keeping a different distance depending on the condition performed. For the *Low* condition, a distance equal or greater than 100 cms is kept, on the other hand, during the *High* condition scenario the distance is kept as close as 50 cms to the user. The rest of the robot's features remain the same for both conditions.

5.5.3.3 Robot Expressiveness

The user and the robot companion are both located in the living room at UH Robot House. The doorbell sounds and the robot reacts by moving towards the hall entrance. The user observed the robot's reaction to the action while this moves towards the hall entrance. The following conditions were evaluated:

- **Low Expressiveness Level** - The robot moves towards the hall entrance, and tries to catch the user's attention using its voice by saying: *"The doorbell has rung. Someone is at the main door"*. The user finishes the interaction by confirming through the robot's screen that the message was received.

- **High Expressiveness Level** - The robot moves towards the hall entrance and tries to catch the user's attention saying the same message as in the previous condition, but this time it increases its expressiveness level by using its upper-torso flashing LEDs.

The user needs to confirm that they checked the main door through the robot's interface. Once the scenario is completed, the users are free to send the robot to another location in the house or use its tray to transport an object. The rest of the robot's features remain the same for both conditions.

5.5.3.4 Robot Assistance Level

The user goes from the living room to the kitchen in order to fetch a beverage bottle from the fridge. The robot detects the user opening the fridge, and starts moving towards the kitchen entrance in order to interact with the user. All participants are free to accept or reject the robot's request and use its tray to transport the bottle from the kitchen to the living room. The rest of the robot's features remain the same for both conditions, just the assistance level feature is modified as follows during each condition:

- **Low Assistance Level** - Once the robot is located opposite the kitchen entrance and facing the user, the robot displays and says the following: *"I hope you enjoy your drink. Let's go to the living room"*. Later, the robot's interface shows two options *"Go to Living Room"* and *"No, Thanks"*. Each participant is free to accept or reject the robot's suggestion.

- **High Assistance Level** - The robot moves towards the kitchen entrance and stops by the kitchen entrance facing the user. The robot open its tray and displays the following: *"Would you like to transport any object to the living room?"*. In this condition, the robot actively offers its help to transport an object to the living room. If the user selects "Yes, Go To The Living Room", the robot will automatically move back towards the living room. Alternatively, the user could just decline the suggestion and avoid using the companion to transport the beverage. An interface example is included in Figure 5.3.

Figure 5.3: Example of the Robot Interface during the High Assistance Level condition

5.5.3.5 Robot Proactiveness

The user is sitting on the living room sofa and decides to read some news from the newspaper. The user goes towards the dining area cupboard where a newspaper is placed inside the drawers, takes the newspaper and comes back to the living room area. The robot detects the user's activity and approaches the sofa area from the dining area, keeping the rest of its features on the same conditions during both versions. These two versions described as follows:

- **Low Proactiveness Level** - The robot approaches the sofa area, and stops close to the user but keeping a social distance. The robot just shows an empathic behaviour by remaining close to the user for the duration of the scenario. The user is free to use the robot in order to check some news on the robot's touch-screen tablet or send the robot to a different location in the house.

- **High Proactiveness Level** - The robot approaches the sofa area, keeping the same distance as in the previous scenario. The robot offers the user to check the online news using its touch screen. The robot asks the following question: *"Would you like to check the latest online news?"*. If the user accepts the suggestion, *"Yes, Please"*, the robot displays the news page based on the user preferences; otherwise, the robot remains close to the user for the duration of the scenario, so it could be sent somewhere else by the user.

5.6 Results and Analysis

As described above, a total of 20 participants performed this *Experiment 2*. The demographic data table for the experiment sample is shown in Fig. 5.1. Each participant was exposed to all different conditions defined for this experiment, therefore, the data is analysed using repeated-measures statistical methods (Field 2013) which are normally applied to within-subject experimental designs. The Spearman's rank correlation coefficient (Spearman 1904) and Wilcoxon signed-rank (Wilcoxon 1945) are an example of non-parametric test used during this research. For the data analysis, SPSS 17 and Microsoft Excel 2007 versions are used and all the tests are conducted with a 95% confidence level.

User	Simple Interface	Advance Interface	Social Approach	Personal Approach	Low Expressiveness	High Expressiveness	Low Assistance	High Assistance	Low Proactiveness	High Proactiveness
User 1	4	4	3	4	1	2	3	4	4	2
User 2	4	5	4	5	3	4	2	4	3	5
User 3	3	4	4	5	4	5	2	4	4	1
User 4	5	4	4	2	4	5	3	4	3	5
User 5	2	4	5	2	4	4	2	4	3	4
User 6	2	4	4	2	3	4	4	5	4	5
User 7	4	3	5	5	5	5	4	4	3	5
User 8	2	3	4	3	4	4	3	4	4	2
User 9	4	5	5	5	3	3	2	5	2	5
User 10	5	4	2	5	5	5	4	5	3	5
User 11	4	4	4	4	5	5	4	5	4	5
User 12	4	5	5	3	5	5	4	5	4	5
User 13	4	5	4	5	3	5	4	5	4	5
User 14	3	5	5	4	5	5	3	5	4	5
User 15	2	4	5	3	3	3	2	4	2	2
User 16	3	4	5	4	3	3	4	5	3	5
User 17	5	5	4	2	3	3	2	5	5	4
User 18	4	5	4	4	3	4	4	5	2	4
User 19	2	4	5	4	4	4	2	3	2	3
User 20	4	4	5	2	4	4	2	5	2	5

Table 5.2: Users responses after interacting with each robot feature and condition (1:Not Comfortable - 5:Very Comfortable)

The experiment data can be found in the Table 5.2 and in the GitHub repository (*Experiment 2 - User Data - GitHub* 2016) for the users responses to the initial questionnaire. First, the Wilcoxon signed-rank test was conducted over every pair of conditions. Both conditions, *Low* or *High*, per robot feature were evaluated against each other, e.g. *Advance Interface* vs. *Simple Interface*, see Table 5.2. The results show that the majority of the robot features presented are significantly different based on the users' data collected, see Table 5.3. The *Approach Distance* and *Robot Proactiveness* features are not significant, although the results are close to the 95% confidence level. This outcome is difficult to explain, even more, when the values are really close to significant. However, the follow-up experiments could reveal whether the outcome is due to an external factor or due to the characteristics of this particular sample.

Robot Feature	Z	Sig.(2-tailed)
Robot Communication	-2.696	0.007*
Approach Distance	-1.843	0.065
Robot Expressiveness	-2.530	0.011*
Robot Assistance	-3.921	0.000*
Robot Proactiveness	-2.458	0.052

Table 5.3: Wilcoxon Signed-Rank Test Values per Robot Feature Evaluated (* Statistically Significant)

To test the general effect of the experimental conditions over each of the robot's features evaluated, a repeated-measures ANOVA test is performed using the data from the Table 5.2. The results show a confidence level greater than 99% based on the Greenhouse-Geisser estimator ($F(2.75,51.03)=7.912$, $p=0.000$), meaning that the outcomes for each result are affected by either of the two conditions defined in the study. The analysis of median values grouped by robot features, see Table 5.4, is depicted in the Fig. 5.4. The results show that the *High* condition was mainly preferred for the *Robot Assistance* and *Robot Protectiveness* features. In addition, at least 75% of the participants found the *High* condition of the *Robot Interface* to be *Quite Adjusted* to their needs. This outcome is going to be considered for the second definition of the model targeted in the next chapter.

The Spearman's correlation coefficient results were included in the table of result (see Table 5.5). This summarises the highest significant correlation and trends found between the user variable defined by the initial questionnaire (see section 4.2.3), and the robot features presented during the experiment (see ssection 5.4). After collect-

User	Simple Interface	Advance Interface	Social Approach	Personal Approach	Low Expressiveness	High Expressiveness	Low Assistance	High Assistance	Low Proactiveness	High Proactiveness
Median	4	4	4	4	4	4	3	5	3	5
Range	3	2	3	3	4	3	2	2	3	4

Table 5.4: Median and Range values for each robot feature and conditions evaluated (1:Not Comfortable - 5:Very Comfortable)

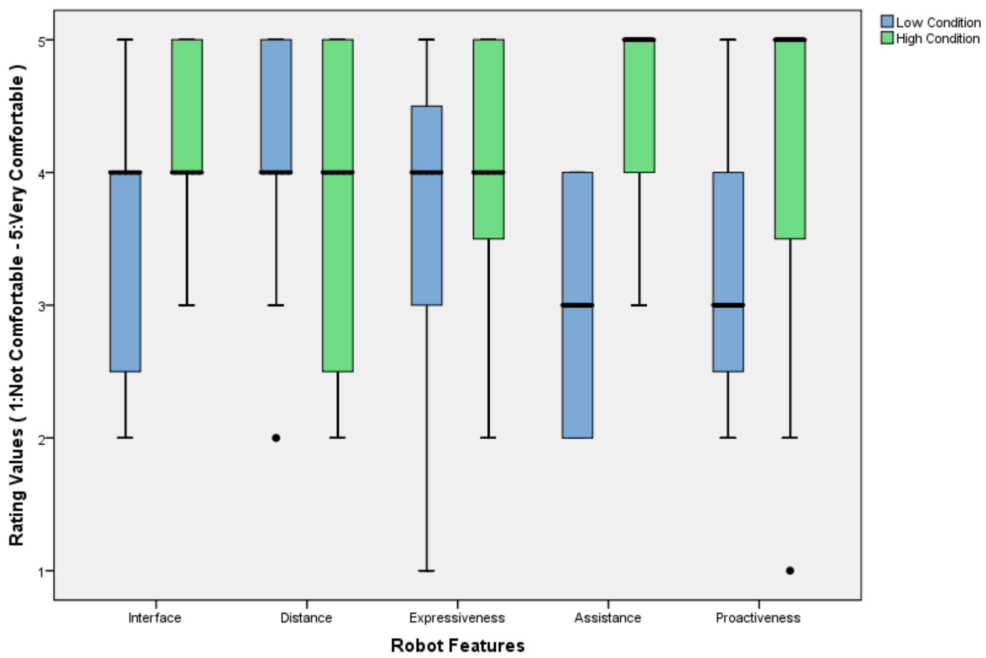

Figure 5.4: Robot Features boxplot for each of the conditions presented (Low and High). The dots represent the outliers for each condition.

ing the users responses to the initial questionnaire, see link (*Experiment 3 - User Data - GitHub* 2016), and the robot features being evaluated by the participants (see Table 5.2), all these variable were compared in order to find significant correlations. This process tries to identify the significant variables that could be used to match users and robot behaviours. The identification of the variables will be a very important step towards the definition of the intended computational behaviour model. In the following sections, the correlations and trends found are individually analysed for each of the five robot features presented to the participants during the experiment.

Scenario	Measured Variables	Condition Affected	Correlation Coefficient	Sig.(2-tailed)
Robot Communication	Pers. Emotional Stability	Simple Interface	-0.479	0.032*
	Robot as Friend	Simple Interface	-0.451	0.060
Robot Approach Distance	Personality Agreeableness	Personal Distance	0.496	0.026*
	Comf. Close Robot	Personal Distance	0.409	0.073
	Comf. Same Room	Personal Distance	0.409	0.074
	Hours Computer/Technology	Social Distance	-0.427	0.060
	Distance Preferred	Personal Distance	0.495	0.027*
Robot Expressiveness	Personality Extroversion	High Expressiveness	0.418	0.067
	Pers. Emotional Stability	High Expressiveness	-0.413	0.070
	Pers. Emotional Stability	Low Expressiveness	-0.479	0.032*
	Previous Robot Experience	High Expressiveness	-0.435	0.056
	Distance Preferred	Low Expressiveness	0.401	0.080
Robot Assistance	Personality Openness	Low Assistance	-0.484	0.030*
	Previous Robot Experience	Low Assistance	-0.535	0.015*
	Previous Robot Experience	High Assistance	-0.436	0.054
	Hours Computer/Technology	Low Assistance	-0.452	0.046*
	Hours Computer/Technology	High Assistance	-0.601	0.005*
Robot Proactiveness	Robot as Friend	High Proactiveness	-0.433	0.057
	Assistance Median	Low Proactiveness	0.506	0.023*
	Technical Background	High Proactiveness	-0.515	0.020*
	Hours Computer-Technology	High Proactiveness	-0.551	0.012*

Table 5.5: Spearman's Correlation Coefficient Summary - Highest significant correlations found between user's characteristics and robot features (* Statistically significant variables)

5.6.1 Robot Communication

Two variables were found statistically significant when calculating the correlation between those and the robot communication features rated by each user. The *Emotional Stability* trait showed a significant negative correlation (r(20)=-0.479, p=0.032*) with the *Simple Interface* condition. This result could be related to the outcomes pointed by Syrdal et. al, where users scoring low in *Emotional Stability* preferred the most mechanical appearance (Syrdal et al. 2007). A possible interpretation would be that these kinds of users would prefer the simplest appearance and functionality of the technology that they are exposed to. It will be interesting to check how this trait performs in the follow-up studies. The second variable, *Robot as a Friend*, was approaching significant(r(20=-0.451, p=0.060), when comparing with the *Simple Interface* too. This negative correlation trend points out a relation between the degree in which a participant wishes the robot to be a friend and the capabilities show by that friend. This can be interpreted as participants showing a higher desired to interact with a robot as a friend would expect the robot capabilities to be as high as possible, which will confirm the initial assumption of linking higher robot capabilities with the first persona described into the system, Jessica (see Section 4.2.2.1).

However, and after analysing the descriptive data for the robot interface feature, 13 users preferred the *High* condition vs. 3 users selected the *Low* condition as preferred, and 4 users rated both equally. In addition, at least 75% of the participants found that the *High* condition was *Quite Adapted* to their needs, as stated before. Based on these results, and the lack of clear definition of significant variables that could explain the selection of one interface condition over the other, the interface's condition to be selected in the next iteration of the behaviour model will be modified, and the *High* condition will be considered to be applied to all personas created in the system.

5.6.2 Robot Approach Distance

A few variables were found statistically significant during the calculation of the correlation between user variables and features. The *Agreeableness* trait shown a significant positive correlation ($r(20)=0.496$, $p=0.026^*$) against the *Personal Distance* condition presented. The personal distance was preferred over the social distance by the most agreeable individuals of the sample, see Fig. 5.5. In this chart, the agreeableness trait values for all participants were grouped into three categories (Low, Medium, High) following the norm values calculated for the TIPI questionnaire (Gosling et al. 2014). This outcome was already pointed out by Takayama et al. when investigating the personal approach of a robot against the users' agreeableness level which represents an external validation for the outcome achieve during this study (Takayama & Pantofaru 2009).

User's comfortableness with robots was found a quite interesting variable to investigate regarding the robot approach. The participants were asked before the interaction about how comfortable they would feel with a robot companion in three different ways: *Being Approached by a Robot, Being Physically Close to a Robot and Being Moving in the Same Room as a Robot.* Syrdal et al. did not find significant differences on the users' comfortableness level depending on the robot behaviour styles shown during their study (Syrdal et al. 2009), however, several trends were found when comparing the user's comfortableness to the different robot approach distances shown in this study. Both variables *Comfortableness when Physically Close to a Robot* ($r(20)=0.409$, $p=0.073$) and *Comfortableness Moving in the Same Room*

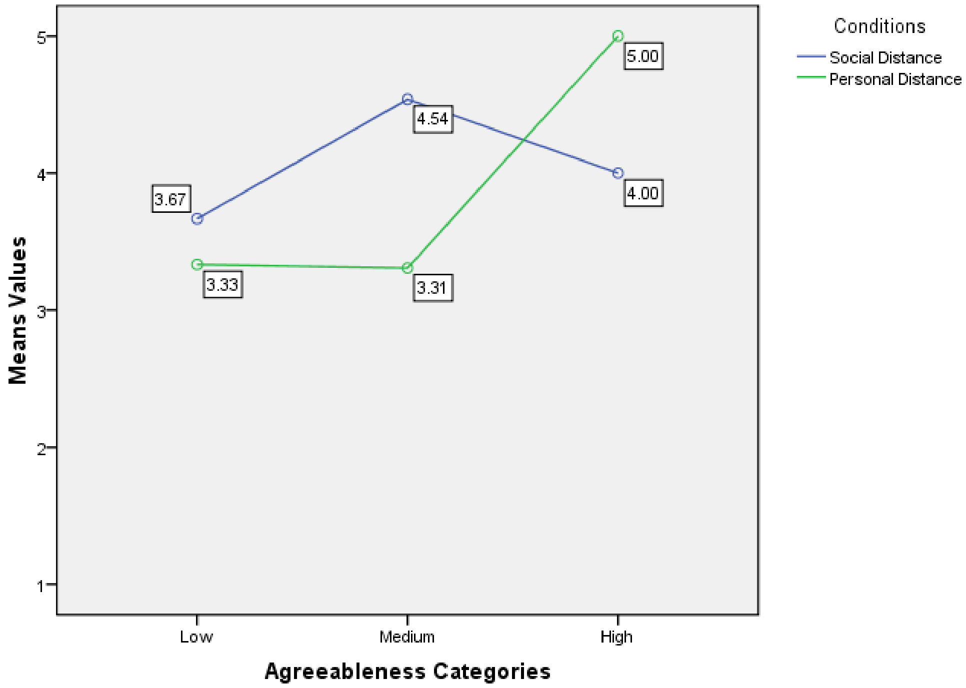

Figure 5.5: Mean Values - Agreeableness Categories vs. Distance Conditions (1:Not comfortable at all - 5:Very comfortable)

that a Robot (r(20)=0.409, p=0.074) were found positively correlated and close to significant against the *Personal Distance* condition. The more comfortable users found themselves in front of a robot, based on their answers during the initial questionnaire, the higher they rated the personal approach during the interaction. This trend seems quite interesting for the behaviour model as people's positive thoughts about how they would feel interacting with a companion, demonstrated to be influential in the way that participants were later rating their level of comfortableness when being close to the companion during the interaction.

The *Number of Hours Using Computer/Technology per Day* variable, which was divided into two categories as mentioned above, was found close to significant (r(20)=-0.427, p=0.060) when compared with the *Social Distance* condition. The negative correlation trend indicates that participants expending fewer hours using technologies a day would prefer to keep a social distance approach over the personal distance. This outcome could be related to the habituation effects study carried out by Koay et al., where the approach distance allowed by participants decreases as they got used to the robot companion (Koay et al. 2007). This effect could be translated to the user's number of hours exposed to technologies and how this could be reflected during the first encounter with a robot companion. Finally, another correlation was found regarding users preferences prior to the experiment and during the interaction in terms of distance approach. The *Distance Preferred* variable was significantly positively correlated (r(20)=0.495, p=0.027*) with the *Personal Distance* conditions. This outcome seems similar to the previous one pointed out between the comfortableness and the approach distance which further supports the relation between people's thoughts about comfortableness being close to a robot and the actual comfort felt during the interaction. Users' experience with robots or background variable were not found correlated with these results.

5.6.3 Robot Expressiveness

During the calculation of the correlation between user variables and the robot expressiveness conditions some variables were found statistically significant. The *Expressiveness* trait was shown close to significant with a positive correlation (r(20)=0.418, p=0.067) against the *High Expressiveness* condition presented on the companion. This trend, between extrovert people preferring more extrovert robots, was pointed by Tapus et al. (Tapus & Matarić 2008), so similar results were expected in this study. As has been depicted on the chart, see Fig. 5.6, it can be stated that users showing a higher level of extroversion tended to find a greater difference between the two expressiveness conditions shown, with the high expressiveness condition being the one usually preferred by this group of users.

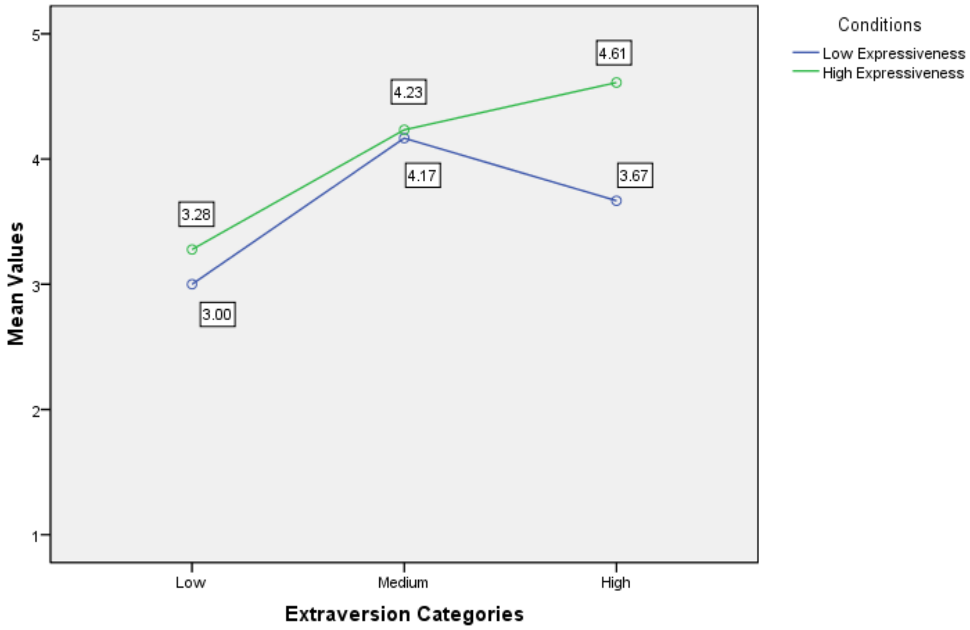

Figure 5.6: Mean Values - Expresiveness Categories vs. User's Extroversion (1:Not acceptable at all - 5:Very acceptable)

The *Emotional Stability* trait was found significantly negatively correlated with both *Low Expressiveness* (r(20)=-0.479, p=0.032*) and *High Expressiveness* (r(20)=-0.413, p=0.070) conditions presented by the robot. We should remember that both conditions were not significantly different from each other according to the Wilcoxon test. However, just the low condition was found statistically significant, with the high condition being close to significant. This outcome is again in the same direction as the results found by Syrdal et al. (Syrdal et al. 2007). Users scoring lower in this trait preferred the most mechanical robot look, so that any sort of expressiveness shown by the companion could be effecting the lower rating in the overall robot expressiveness. One more trend was found as well, with the variable being close to statistically significant. The *Previous Robot Experience* indicated a negative correlation ($r(20)=-0.435$, $p=0.056$) with the *High Expressiveness* condition. This suggests that inexperienced users tend to evaluate the high robot expressiveness more positively when they are asked about how comfortable they found that robot behaviour.

In summary, a few interesting trends were found in the direction that expected regarding personality traits and its influence over the robot personality preferences. These outcomes are directly connected to the initial assumption in which the robot's acceptance could be affected by users' personality and higher levels of extroversion would be associated with the acceptance of more expressive robot companions. Additionally, the negative correlation observed between the *Distance Preferred* and the *Low Expressiveness* condition ($r(20)=-0.401$, $p=0.080$), make the author think about the influence of people attitudes towards robots and their tendency to evaluate their behaviour more negatively (Nomura et al. 2008) (Syrdal et al. 2009).

5.6.4 Robot Assistance Level

After analysing the two different *Assistance Level* conditions shown in the robot, it was noticeable that the *High Assistance* condition was highly rated by the majority of the users, regardless of any of the variables or user characteristics that were measured. This emphasises that users from this sample will prefer the highest level of assistance implemented on the robot regardless of the assistance level requested by the pre-experiment questionnaire. On the analysis of variables, several significant linear relationships were found among the data. For instance, the personality trait *Openness* shows a significant negative correlation ($r(20)=-0.484$, $p=0.030$*) compared to the *Low Assistance* condition of the robot. Based on this sample, where a big percentage of people had little or non-experience of interacting with companions before, the fact that the companion did not offer its help to carry a drink during the scenario could have affected their desire to be involved in a new experience of interacting with a robot. Follow-up studies could confirm this finding, as it cannot be determined based on just these outcomes.

A second variable, the *Previous Robot Experience*, was found significantly negatively correlated with both assistance level conditions. The *Low Assistance* (r(20)=-0.535, p=0.015*) and the *High Assistance* (r(20)=-0.436, p=0.056) present a moderate negative linear relationship, close to significant in the case of the *High* condition. Overall the high assistance condition was rated consistently higher than the low assistance condition by the majority of the participants. According to the results, the higher the previous participants' experience interacting with robots is, the bigger is the difference between *Low Robot Assistance* and *High Robot Assistance* values. This outcome, depicted in Figure 5.7, could be related to the fact that these users could have higher expectations of the robot behaviour to be fulfilled than the rest of the participants in this sample.

A similar result was presented when analysing the *Number of Hours Using Computer/Technology per Day* which showed a significant negative linear relationship with both conditions, *Low Assistance* (r(20)=-0.452, p=0.046*) and *High Assistance* (r(20)=-0.601, p=0.005*). The same interpretation given for the *Previous Robot Experience* can be used to explain this result. A total of 19 out of 20 users selected the *High* condition as preferred over the "Low", which indicates the need of modifying the initial behaviour model in order to define the *High Assistance* condition as default for all users interacting with the robot. These outcomes dif-

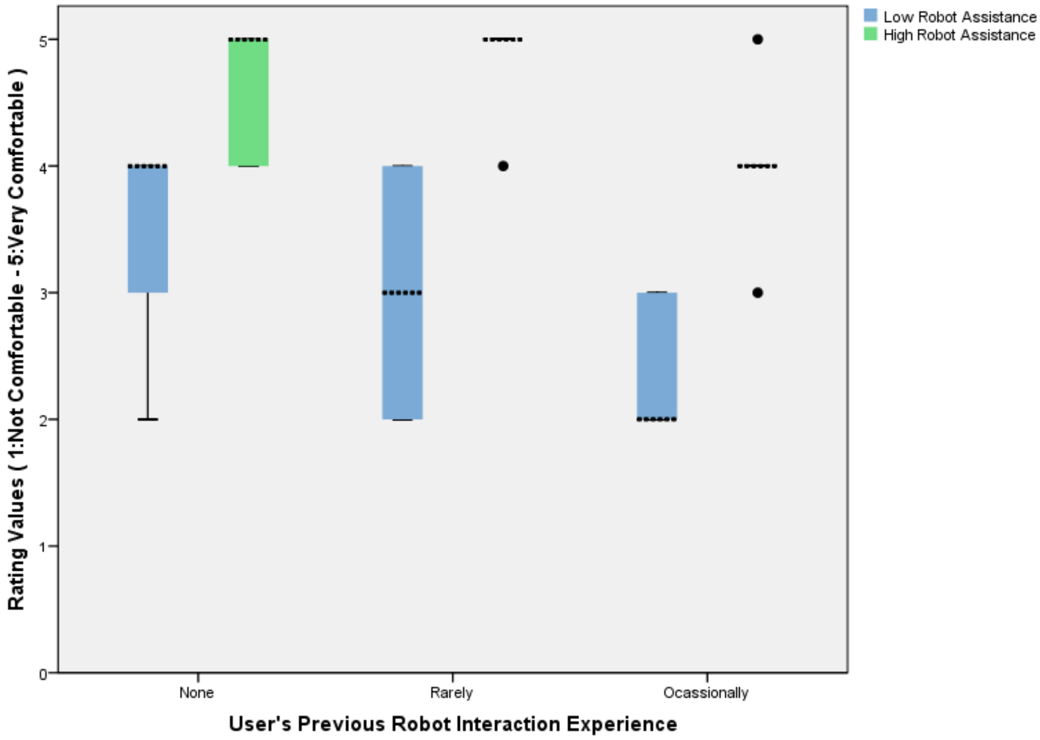

Figure 5.7: Robot Assistance vs. User's Robot Experience Boxplot. The dots represent the outliers for each condition.

fer from the initial expectations where the assistance level desired was expected to be determined by the assistance level indicated during the pre-experiment questionnaire. The experiment outcomes indicate that the participants tended to rate higher those robot behaviours showing a greater number of features, regardless of the user's characteristics and declared preferences regarding the robot assistance feature.

5.6.5 Robot Proactiveness

The users' variables were evaluated against the robot proactiveness feature in order to find some correlations to explain the selection of one condition over the other. The *Robot as a Friend* variable was found positively correlated (r(20)=-0.433, p=0.052) when compared to the robot *High Proactiveness* condition. This negative correlation, although being just close to significant, shows a trend between this variable and the *High* condition which differs from the initial assumptions. The participants were expected to have a positive correlation between the *Robot as a Friend* and the *High Proactiveness* based on the definition of the first persona, Jessica 4.2.2.1. However, this opens up a new direction in the discussion about how the robot's proactiveness should be interpreted depending on the robot role preferences indicated by the user. People considering the robot as a friend might prefer not to be interrupted by the robot during certain situations, e.g. when reading a book or newspaper, so the user is the responsible for initiating the interaction instead.

Another variable, the *Assistance Median*, calculated through all assistance values specified by users in the pre-experiment questionnaire, see Table 5.6, was found significantly positively correlated ($r(20)=0.506$, $p=0.023^*$) to the *Low Proactiveness* condition rating during the experiment. Users requesting a higher level of assistance prior to the start of the interaction tended to rate the "Low" condition higher. This suggests that these users were still happy when the robot that just showed an empathy behaviour and did not proactively start the interaction during the scenario evaluated. Finally, the variables *Technical Background* and *Hours Using the Computer/Technology per Day* were both found significant negatively correlated to the proactiveness robot feature. Therefore, it could be stated that more technical users preferred a lower proactiveness level shown by the robot during the experiment. This outcome does not match some of the initial expectations regarding *Background* and *Robot's Proactiveness* preferences. Based on the first definition of the model, more technical people were expected to prefer the higher proactiveness level over the lower level, as they are often exposed to technologies showing a more proactive behaviour in different situations and contexts. This interesting outcome is suggesting that the proactiveness level would need to be modified for the personas defined in our system in the next iteration of our model.

	User1	**User2**	**User3**	**User4**	**User5**	**User6**	**User7**	**User8**	**User9**	**User10**	**User11**	**User12**	**User13**	**User14**	**User15**	**User16**	**User17**	**User18**	**User19**	**User20**
Median	2	1	3	3	2	2	2	3	2	2	1	3	3	3	2	2	2	2	1	1
Range	2	2	2	1	2	2	2	2	2	2	2	1	2	2	2	2	2	2	2	2

Table 5.6: Median and Range values for the *Assistance Level* median wished by the users (1:Low Assistance - 3:High Assistance)

After a closer look at the results for the robot proactiveness, a new trend was identified with some participants preferring the lower level of proactiveness and still the higher level of all other features during the interaction, see Figure 5.8. This result differs from the initial definition of personas and behavioural model where young people should have preferred a high level of proactiveness shown by the robot companion. This indicates the need of creating a new persona and expand the initial definition of the computational behaviour model in order to cover a wider range of participants.

In summary, it was really difficult to find clear patterns that explained why certain robot features were rated higher than others in the first attempt to use the findings to defined our computational behaviour model. In this section, the main outcomes regarding how users rated the robot behaviours presented during this scenario were presented. This helped to understand people's preferences and point out the difficulties of modelling people in HRI studies. The size of the sample could be a factor to consider, but it is already known the problems of recruiting participants for HRI studies, even harder when trying to balance the sample in

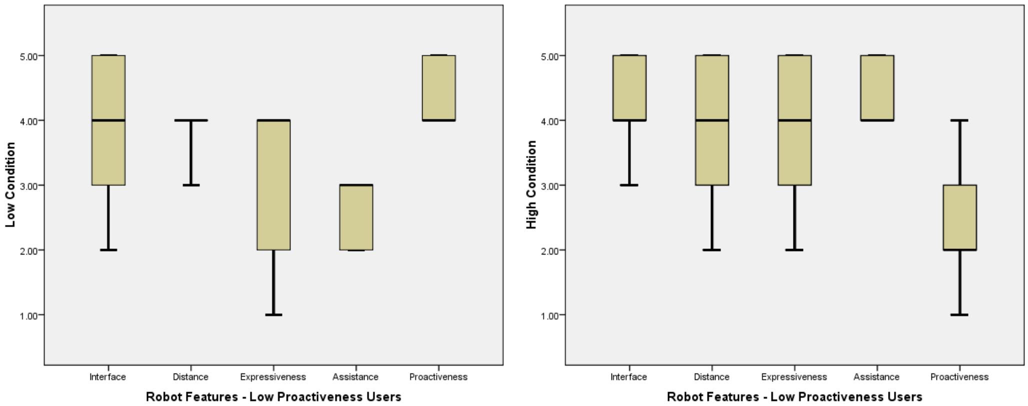

Figure 5.8: Median values for the set of users (N=4) rating *Low Proactiveness* condition higher than *High Proactiveness* (1:Not acceptable at all - 5:Very acceptable)

terms of gender, age or background. However, and given the results, it could be concluded that trends and modifications to the system were found and the follow-up study will integrate these findings after the expansion of the initial set of personas defined in the model.

5.7 Discussion and Conclusion

A study investigating the concept of personas field was conducted at the UH Robot House. The main purpose was to evaluate different robot features against users of the system in order to determine the set of variables that could influence the selection of a robot behaviour over a similar one presented. The persona-based model to be defined is intended to enhance the first interaction between users and a robot companion in a home environment. An initial set of personas based on previous HRI studies from our research group was defined. The matching between users and these personas will make possible the characterization of the companion's behaviour during the interactions. Therefore, the first target was to evaluate potential users of the system interacting with a robot companion, Sunflower, in order to learn about their preferences on each of the tasks that were presented during the experiment. The information collected and the outcomes obtained are an important stepping stone towards our goal of developing a robot able to adapt its behaviours based on the persona that each individual matches.

The 20 participants performed a set of HRI scenarios where the several robot features were presented, see Section 5.4. These features were modified based on two well-differentiated conditions characterised as mostly *High* and *Low* levels. The introduction of an intermediate condition of each robot feature, e.g. 'Medium', could have led to the definition of similar scenarios where participants would have not been able to identify any differences between the robot behaviours presented. During the experiment, each of the robot's behaviours shown was rated by the users through the 5-points rating scale defined in the questionnaire (see Appendix C.5). These rates were base on their personal observations and preferences when interacting with the robot companion. Overall, some interesting correlations and tendencies were found among the data analysed that are going to be taken into consideration for the next iteration of the system. The findings obtained after the *Experiment 2* analysis contributed to address the research questions covered during this chapter.

Firstly, users sharing a similar characteristic, i.e. personality, background or previous experience with robots, were expected to rate similarly some of the robot behaviours shown during the experiments. A few examples were extracted from the data to represent the difficulties of finding a pattern in this regard, see Figures 5.9 and 5.10. According to the results obtained after analysing the sample, it was not always possible to predict certain users' preferences when interacting with the companion based on similarities of individual users' characteristics, which will answer the *RQ2* based on the data and sample analysed. Therefore, the first hypothesis, *H1*, cannot be supported. In HRI studies, some external factors could be out of the researcher control and affect users' evaluation of their personality, preferences or tasks performed by the companion. However, some robot features were found correlated to a subset of users' variables which will be used for the definition of the next version of the computation behaviour model following the iterative methodology. Nevertheless, the difficulties of creating a model based on a wide range of variables could be expected, so this first study was always considered as a learning process towards the creation and the understanding of the behaviour model to be developed.

During the analysis of results, it was found that the initial assumptions defined on the behaviour model, see Section 4.3.1, did not totally match the findings of this experiment. The number of personas needs to be expanded as several participants from the sample seem to prefer a combination of robot features associated to both personas, Jessica and Matthew, see section 4.2.2. This expansion was something expected as part of the first iteration of the system, so it can support our second hypothesis *H2*. Based on the results, the definition of a new persona will be presented in the following chapter. This new persona in the model will contribute to describe the new version of the behaviour model based on the set of personas defined in the system. In addition, some robot features' conditions, *Advance Interface* and *High Assistance Level* were highly positively rated by the majority of participants. This result indicated that the behaviour model should be modified so these preferred conditions should be kept constant for any of the personas defined into the system. These modifications are expected to improve the performance of the system to match users' preferences during its next iteration. This first study provide a great insight into the difficulties that could be faced during this investigation of the persona technique in HRI studies as part of a computational behaviour model.

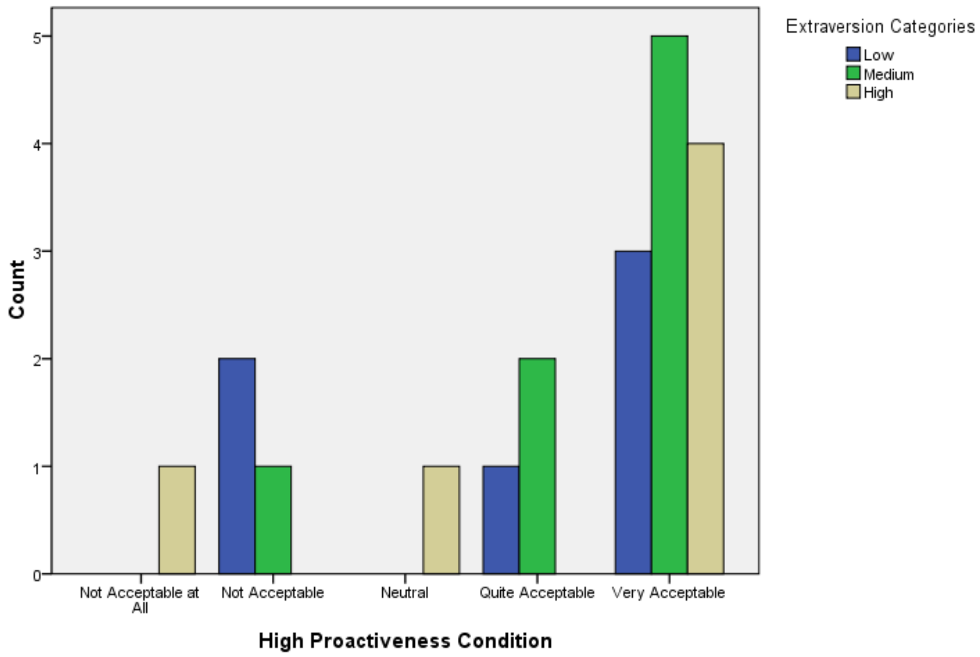

Figure 5.9: *High Proactiveness* condition frequencies grouped by users' extroversion. Represent the variability of data between users with similar extroversion values (1:Not acceptable at all - 5:Very acceptable)

Secondly, an initial behaviour model based on the two personas created for the system was created. This initial model was proposed as a guideline for the experiments' design, and it was definitely expected to change and to be expanded afterwards for the follow-up experiment. One of the main objectives was to reduce the number of variables and determine any sort of association between users' variables and preferred robot features. It was not possible to define a clear pattern that allows us to predict users' preferences based on the set of users variables studied, however, it was possible to extract a subset of variables that could explain the eval-

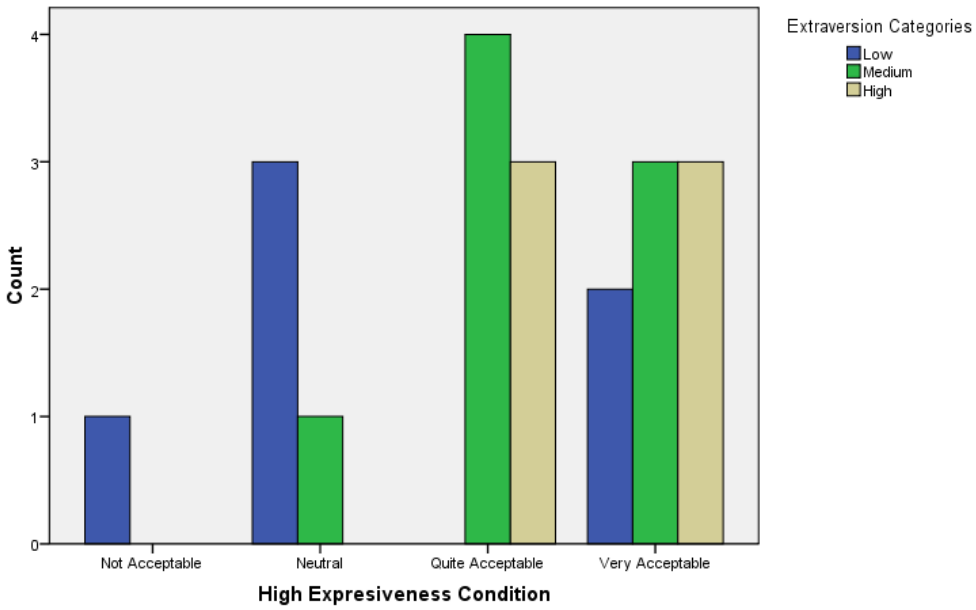

Figure 5.10: *High Expressiveness* condition frequencies grouped by users' extroversion. Represent the variability of data between users with similar extroversion values (1:Not acceptable at all - 5:Very acceptable)

uation of certain of the robot behaviours presented to the participants during this study (see Fig. 5.5). The identification of these significant variables will guide the definition of the model in later stages and will also answer *RQ3*. According to the outcomes, a few variables were found statistically significant to explain why users rated some condition higher than others during the evaluation of the scenarios. The following findings could be summarised in terms of the users' variables evaluated:

- *Age, Gender or Education Level* were not considered relevant for the purpose of the study, but after analysing the data no correlation were found regarding this variables. On the other hand, *Technical Background* and the *Number of Hours using the Computer/Technology a Day* were shown influential in determining the preferred behaviour during the evaluation of the *Robot Assistance* and

Robot Proactiveness scenarios.

- *User's Personality Traits* were found influential across the majority of the robot features evaluated. It seems that *Extroversion, Agreeableness, Emotional Stability and Openness* would be the traits to consider when defining the behavioural model. The *Robot Communication*, *Robot Approach Distance*, *Robot Expressiveness* and *Robot Assistance* contain personality traits among the variables that could help to determine users' preferences during the interaction. Some of the correlations found were just trends as they were not found statistically significant, nevertheless, all outcomes should be considered due to the reduced size of the sample and the limitations that this could offer. At the moment, it would be difficult to conclude the degree to which these traits will affect the final robot behaviour, but it is possible to foresee that these variables will be influential and considered in the final computational behaviour model based as suggested from previous studies done in the same area.

- The *Previous Experience with Robots* also played an important role when rating the *Robot Expressiveness* and *Robot Assistance* scenarios. Expectations of these sorts of users seem to be higher which make them rate the robot features lower than most inexperienced users.

- *Comfortableness towards Robots* was found to be an interesting variable when rating the *Robot Approach Distance* during the experiment. Participants' thoughts, as indicated in the pre-experiment questionnaire, about how comfortable they would feel interacting at a personal or social distance from the robot seem to be related to their preferences after interacting with the robot companion. However, the trend found needs to be investigated in the next experiment, *Experiment 3*, to determine the importance of this outcome.

- The *Robot Role* has been shown as relevant for a few of the robot features studied. The way users perceive the robot seems to influence how that they rated the *Simple Interface* and *High Proactiveness* conditions. This variable would need to be considered for the next study in order to validate the tendencies presented during the analysis of this experiment data.

- The median value of the *Assistance Level* required by users on ADLs, see Table 5.6, was found relevant for the evaluation of the *Robot Proactiveness*. The assistance required was measured during the pre-experiment questionnaire and the median value calculated to determine the overall assistance level wished by each user. These outcomes could be interpreted as follows, users requiring a higher level of assistance across the different activities evaluated were rating the *Low Proactiveness* higher than the rest of users. However, this statement has to be further investigated as it could be affected by other factors or, perhaps, the size of this sample. In general, the robot *Assistance Level* presented was highly rated for the highest of the condition which seems to indicate that this robot feature should be set as default in the next version of the model.

- The *Approach Distance* preferred by users was found relevant for the evaluation of the *Robot Approach Distance* and the *Robot Expressiveness*. This preference was asked on the pre-experiment questionnaire in order to compare users' thoughts before the experiment to users' thoughts after the interaction with the robot. Based on the data, 55% of the users did not change their initial preference, 25% changed their preferences after the interaction and 20%

rated both approach distances equally. This trend seems quite interesting to investigate as users could have already a predefined idea of the interaction that could be influencing the first encounter with the robot.

Following the analysis of the data, some of the results could be defined in line with the expectations. On the other hand, some limitations of the first model suggested were expected due to the definition of just two personas which does not represent a wide enough range of users in the system. It was observed that a third persona needs to be defined in the model in order to represent users who preferred a less proactive robot behaviour during the interaction, but who still preferred the *High* condition for some of the robot features. As a key note, the sample was composed of a majority of young people so the results could have been affected by that. As reported by Scopelliti et al., young people have more familiarity with technology and a friendly idea of robots (Scopelliti et al. 2004). One interesting result was found for the *High Assistance Level* condition, which was highly rated (M=4.5, SD=0.607) by the majority of users, even when some they indicated a lower assistance level required in the pre-experiment questionnaire. Both conditions, the *Low* and the *High* assistance level, were presented in a random order to each of the users in order to avoid the counter-effect. Participants prefer the robot to assist them during carry and fetch tasks, regardless their assistance level required to perform this task. This result is related to how people see robot companion and their assistance role in future homes (Dautenhahn et al. 2005). This will be taken into account for the next iteration where the *High Assistance Level* will be the default condition for all users. The same situation was found with the *Advance Interface* mainly preferred by all users in the sample. As mentioned before, these considerations are expected to improve the overall performance of the system and adapt the robot behaviour to a wider range of users.

It could be concluded that the study conducted helped acquire a better understanding of the user's needs and, at the same time, it was possible to learn about the difficulties of modelling user preferences when interacting with a robot companion. The difficulties are mainly due to the diversity of users and the lack of patterns that could explain the evaluation of certain robot behaviours. After the experiment, it was easier to narrow the number of variables to incorporate into the model and the user characteristics that should be taken into account in order to match each participant with a persona. Nevertheless, more investigation is needed to define the model definition and understand the user's preferences when interacting with a robot companion. The knowledge gained and the findings from this study will be used to perform the next study in the upcoming chapter.

5.7.1 Experiment Limitations

As mentioned earlier, the results could be affected by the type and size of the sample, where the majority of the participants were relatively young and technologically experienced people. Nevertheless, these kinds of participants were still valid for the purpose and objective of this study. A more focused sample might have shown a clearer picture than the evaluation carried out, however, this could not be guaranteed. The results will guide the future work, however, the outcomes achieved should not be generalised. A different sample could provide different results to the achieved during this study, as already mentioned when pointing the number of factors affecting HRI studies. Recruiting a varied and balanced sample is always difficult, so researchers must learn to interpret the outcomes and consider their limitations when applied to a different environment.

The main purpose of this research was to verify the viability of building a computational behaviour model for human-robot interaction based on the concept defined by Alan Cooper more than a decade ago. Based on the findings of this experiment, it could be challenging to create a precise and general personas computational behavioural model, however, the data collected will use to define the initial model targeted to best of the author abilities. A great amount of data was collected that will be used to redefine and improve the next version of the model to be used in future studies at the UH Robot House. As discussed, some of the outcomes were expected based on previous researches, some of them differed from the initial thoughts, and other results were totally unexpected, opening up new discussions about the ways to interpret data and define the model. This investigation should be a constant learning process to change the way of thinking and improve the future research steps.

It could be concluded that some of the initial assumptions need to be modified to incorporate the outcomes of this experiment. Firstly, the model will be expanded to include new personas, and the ones previously defined will be modified according to the tendencies that were found during this study. Secondly, the set of user variables to be considered for the interpretation of users' preferences when interacting with the robot were reduced, which will positively contribute to determine the variables to be used for the match between users and personas in our system. Nevertheless, some of the previous variables might be re-introduced if they are found relevant in future experiments as part of the iterative development process. Finally, the same process will be followed and the new definition of the model will be evaluated trying to reveal whether the new expectations are going to be fulfilled in the future experiment. It becomes clear that the original idea of defining a persona computational behaviour model to allow a robot to adapt to users is more complex than initially thought. However, a set of tendencies were found which makes the author still believe that the computational behaviour model based on the persona technique can still be achieved and contribute to improve some of the current HRI problems pointed out during this dissertation.

Chapter 6

Evaluating Personas in Human-Robot Interaction Studies - Second Iteration

6.1 Introduction

This chapter presents the preparation, evaluation and analysis of the *Experiment 3* performed during this research, but the second evaluating the concept of personas within HRI studies for its integration into the computational behaviour model targeted. Once again, the UH Robot House and Sunflower were used to perform this experiment, as for the previous *Experiment 2*, see Chapter 5. On this occasion, the participants (N=35) are evaluated against three different scenarios where the robot will adopt the behaviour suggested by the three different personas defined in the system. It is expected that the preferred scenario for each user corresponds to the one defined by the persona that appears a match to the user. The following lines will describe the experiment's design process and outcomes obtained after analysing the data collected. The research questions RQ3 and RQ4 will be addressed in this chapter according to the outcomes obtained during the experiment. The *Experiment 3* was performed under Ethics Approval protocol number a1213-13(2).

In the previous experiment, the user variables that might explain the preference of certain robot behaviours over others were investigated. The outcomes were useful to reduce the number of variables that should be looked at during the definition of the model and to find out whether there was a need to expand the initial behaviour model in order to represent a different sort of user in the system. Based on the previous findings, the data was analysed and the initial specification of the model was modified before being tested during this experiment. The modification of the initial behaviour model for robot companions and the number of personas used to match the participants to the model are the main changes to explore during this chapter. This adjustment should represent a step forward towards the creation of a model capable of adapting robot companions' behaviours to the needs of a wider range of users during the first interaction. However, it is important to be cautious and consider the limitations of the experiment and the methodology used, see Section 6.8.1. In the previous chapter, the difficulties finding patterns to define the computational behaviour model were pointed out. In this chapter, this limitation must be considered too when evaluating and analysing the data collected.

This chapter is organised as follows. Section 6.2 describes the main purpose of the study and expectations. In section 6.3, the research questions are presented together with several sub-questions associated with each of the main research questions addressed. Section 6.4 presents the system description where the experiment will take place and the robot companion to be used and the features to be shown to the participants. The section 6.5 describes the new model defined and the persona created after the outcomes obtained in the *Experiment 2*. The following section, Section 6.6, details the experiment procedure, including participants and the conditions which those were exposed to during the evaluation of the system. In section 6.7 the main findings are described based on the analysis of data carried out upon the data collected. Finally, section 6.8 discusses how the outcomes of this experiment will be used for the next iteration of the system and the conclusions after performing the experiment described in this chapter.

6.2 Purpose of the Study

The purpose of this study is to evaluate the new iteration of the computation behaviour model after introducing the modifications suggested by the previous experiment's results, *Experiment 2*. The participants will be exposed to a set of scenarios in a realistic environment, the UH Robot House, where they will interact with the companion and evaluate its behaviours. The robot will show three different behaviour sets corresponding to the three different personas that will compose the behaviour model based on the previous research. As already mentioned, each persona will be used to guide the robot behaviours in each particular situation occurring during the interaction between users and the robot companion. The results are expected to show how users are more akin to one of the personas, i.e, personality, comfort interacting with robots or robot role, as they would prefer the robot's behaviour associated with that persona instead of the other behaviours to be shown. This assumption will be answered at the end of the chapter and based on the outcomes of the experiment to be performed.

For this new experiment, a new persona definition is introduced into the computational behaviour model investigated. The previous experiment's results suggested the creation of this new persona in order to cover a wider range of users to interact with the robot companion. A group of 4 participants preferred the robot to be shown a lower level of proactivness during the interaction. Defining and integrating a new persona into the model is expected to fulfil the gap found during the analysis of data in the previous experiment. This modification is expected to help in the categorization of participants across the three different scenarios that will be presented during the experiment described in this chapter. The association of users with personas and the correspondent robot behaviour is the key part of this experiment and the outcome should answer the research question defined. The lack of patterns found in the previous experiment make the expansion of the model a good way to further investigate the problem detected and apply the iterative methodology selected for this research. The modifications introduced into the system are based on the previous outcomes, and so, expected to help defining a better match between robot behaviours and user variables to identify user preferences interacting with robot companions.

In summary, this experiment is intended to determine how close the second model approach is to the initial expectations and how this could be further improved to suit HRI studies. The research was focused on investigating the concept and providing a better insight into the use of the personas technique as a computation behaviour model in the area of smart homes and robot companions. This experiment will help answer one of the main research questions defined in this research, *RQ4: Which are the advantages and disadvantages of integrating the concept of personas into the development process of a computational behaviour model for robot companions in smart homes?*. It was considered that identifying the advantages and disadvantages of the approach will positively contribute to future research in the field. Users expect social skills to be already integrated into robot companions when first interacting, the achievement of robot behaviours' initial adaptation based on users' characteristics through the identification of the sort of users interacting with the system is a challenging, but an exciting approach to be investigated.

6.3 Research Questions

It is important to persist on the idea of creating a computational behaviour model for HRI based on the concept of personas, however, the limitations found in the *Experiment 2* must be considered. The model should help to close the gap between users and robot companions during the first interaction as robot behaviours will be modified to match the user's expectations of the system. Based on previous results, it was not possible to define yet a clear subset of user variables to explain the relation between user characteristics and robot behaviours preferred during the interaction. In addition, users preferring the same robot feature were not always found akin to other users selecting the same robot features, when comparing the user variables evaluated. The experiment's sample or other external factors could have influenced the human-robot interaction and it could be difficult to tell. Nevertheless, the outcomes from the previous experiment suggested the creation of a new persona in order to expand the combination of robot behaviours shown across the different tasks performed at home. This new behaviour's combination and its association to each persona defined in the system should contribute to getting a balanced distribution of users when they are asked about their preferred scenario from the ones presented during this study.

As mentioned before, an iterative methodology is being followed in an attempt to collect the necessary data to define the computational behaviour model targeted. This is the reason why *RQ3* will be addressed again during this experiment in the second attempt at refining the model to better reflect the range of users that the system could interact with. It is necessary to investigate if there is an improvement on the performance of the model, so as to be able to determine the path to be followed in future steps of this research. A set of sub-question have been defined after the extension of the number of personas created and the extension of the robot's responses to the different situations that could take place during the interaction. They are created to focus the efforts during the analysis of data from this experiment. The following are the research questions, and sub-questions, to be addressed during this chapter:

RQ3: *Which are the most significant variables found that could help identifying the users' preferences and needs so we are able to adapt the system appropriately?*

1. Has the expansion of the number of personas helped to classify the participants and associate them with one of the personas defined?
2. Has the number of variables to be considered in the model been increased or decreased after analysing the results?

RQ4: *Which are the advantages and disadvantages of integrating the concept of personas into the development process of a computational behaviour model for robot companions in smart homes?*

1. How could the HRI field use personas to develop a socially assistive system with a robot companion in a smart home?

2. Which limitations have been found during the investigation that need to be considered for future research on this topic?

Hypothesis: Based on the previous research questions, the following results could be hypothesised after running the experiment and analysing the data collected:

1. H1 - The expansion of the number of personas defined on the system will contribute to better classify the users and identify their preferences when interacting with a robot companion at home.

2. H2 - Users selecting the same preferred scenario will have common characteristics that will allow us to identify patterns to be incorporated into the definition of the computational behaviour model.

6.4 System Overview

The same architecture and system described in section 4.4 has also been adopted for this study. In the same way, the UH Robot House has again been the naturalistic environment selected to perform the investigation. The participant's demographic information, personality and robot interaction preferences were gathered before the experiment through a closed format questionnaire, see section 4.2.3. The questionnaire was integrated into the personas module created as part of the system definition and the users were able to fill it in using a desktop application. Two different sessions, performed in two different days, were defined for this experiment, see section 6.6.1 for further details. During the first session, the users were exposed to the same scenario in three different occasions. The robot behaviour was modified according to the behaviour associated with each of the personas defined in the second model approach, see section 6.5. The participants individually rated the overall scenario performance according to their preferences and feelings. At the end of the experiment, a post-questionnaire was completed to collect information about their preferred scenario.

All scenarios were video recorded in order to show participants their interaction during the second session of this experiment. This second session was run to collect extra information and verify the results obtained during the first session of this experiment. The questionnaires are attached as Appendix C for further information. As in the *Experiment 2*, all the data collected are going to be to investigate the behaviour model aimed and understand the users' preferences and needs when interacting with a robot companion at home. Starting from an initial assumption, the model is being redefined based on the results after each experiment. An example of one of the scenarios performed is attached, see Figure 6.1. It is possible to appreciate how the experimental area resembles a normal living room and kitchen environments and it was arranged to facilitate the interaction with the robot and make users as comfortable as possible.

The Sunflower companion (see Fig. 4.3) is the companion used for the study as well. Also, two conditions, *Low* and *High*, are specified for each of the robot features defined in section 4.3 this time. However, and based on the *Experiment 2* findings, the *Robot Communication* feature will be set to the "High" level condition by default, see the section 6.5 below for further information. The definition of personas must be used to guide the specification of the robot behaviours that will be shown to the user during the interaction. The persona should be represented on the way that the robot behaves in order to achieve its goals when using robot companions. The incorporation of a new persona to the model makes the definition of distinct

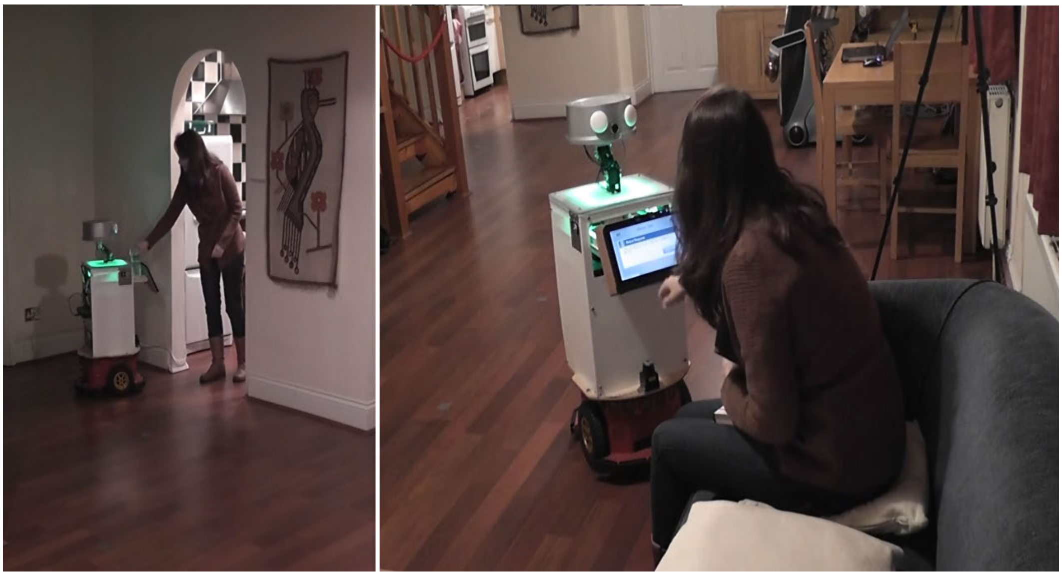

Figure 6.1: Scenarios example with Sunflower in the UH Robot House. A user taking a drink and using the robot to transport it towards the living room.

robot features and scenarios a bit harder. The scenarios defined in this experiment describe the interaction between the user and the robot companion during a set of daily living tasks. The following are the features displayed by the robot during the performance of this experiment. Some of the features defined were suppressed and others modified based on the *Experiment 2* outcomes, see Section 5.6:

- Robot Communication
  - Advance Interface (High Condition) - The interface will include several menus where the user could modify their selection over the preferences chosen in the initial questionnaire. This option will give the user a better control of the system whether they decide to change some preference during the interaction. The lowest condition of this feature has been suppressed based on the preferences shown by the majority the participants in *Experiment 2*.

- Verbal Communication - This is a common feature to be enabled for all participants, so it is neither a Low or a High condition. The robot will be able to communicate commands through its speaker. This condition has been activated by default, as it was accepted by the majority of participants in *Experiment 2*, however, the user will be able to deactivate it at any time, and all messages will be still displayed on the tablet PC.

- Robot Approach Distance
  - Low Condition (Social Zone) - The robot companion will keep a distance greater than 100 cms when approaching the user. This condition has not been modified in order to be re-evaluated during this study.
  - High Condition (Personal Zone) - The robot companion will keep a distance of 50 cms approximately when approaching the user. This condition has not been modified in order to be re-evaluated during this study.
- Robot Expressiveness Level
  - Low Condition - The robot companion will reduce its expressiveness level by avoiding flashing its torso lights or moving its head and torso from left to right when interacting with users in order to catch their attention. This condition has not been modified in order to be re-evaluated during this experiment.
  - High Condition - The robot companion will use a combination of head and torso movements, left to right, and flashing light on top of its torso to catch the user's attention during the interaction. Both the head and the torso movements have been newly introduced for this study. These

improvements will make possible to enhance the robot's expressiveness in order to increase the differences shown between the low and high condition of this robot feature.

- Robot Assistance Level
  - High Condition - The robot companion will proactively offer to transport an object for the user from one location to the other. The low condition of this feature has been suppressed based on the 95% of users that selected the *High Condition* as their preferred one.
- Robot Proactiveness
  - Low Condition - The robot companion will ask the user for confirmation before executing a task. Based on the current status of the system the robot could determine the action to execute next but without user's confirmation, this will not be executed. This condition has not been modified in order to be re-evaluated during this experiment.
  - High Condition - The robot will make its own decisions based on the status of the system. Depending on the task the user will not need to confirm the action and the robot will execute the task after advising the user about its next movement. This condition has not been modified in order to be re-evaluated during this experiment.

6.5 The Behaviour Model - Second Iteration

After the *Experiment 2* analysis of results, section 5.6, it was concluded that the model needed to be expanded in order to represent a set of users who preferred a combination of robot features different to those proposed by the initial definitions of the model. A total of four users preferred the companion interacting with a lower level of proactiveness as they felt uncomfortable when the robot decided to interrupt them or made a decision on its own, see section 5.6.5. After a closer look to these users' data, it was observed that they scored a high value for the variables identified as significant for the evaluation of the *Robot Proactiveness* level (see Table 5.5). These variables are: the *Robot as Friend* (Median=4.0, Min=1.0, Max=5.0), *Median Assistance* (Median=2.5, Min=1.0, Max=3.0), the *Technical Background* (all these participants got a technical background) and the *Hour Using the Computer/Technologies per Day* (Median=10.0, Min=1.0, Max=24.0). Taken this set of preferences into account, the new persona was defined in order to capture the preferences of these users when interacting with the robot:

6.5.1 A New Persona - Simon

Figure 6.2: Simon

Simon [1] is a 35-year-old businessman working in an international technology company in the middle of Bristol. He moved to this company 2 years ago and since then he has made quite a lot of progress thanks to his great work inside the department. He is really appreciated in the company and is a great fellow worker. He is a bit introverted about his own matters, but he can be easily approached whenever you need him as he will be keen on helping you. He is considered an excellent communicator and eloquent person.

[1] Image Source: http://upload.wikimedia.org

He lives with his family in a 3-bedroom house outside Bristol. He got married 5 years ago and the couple is expecting their first baby in the next few months. He commutes every day by train and he uses this time to prepare his tasks at work. He is always quite busy as he is acquiring more and more responsibilities inside the company. He is always reading the news and getting updated about the latest in technology. This helps him to take better decisions as he always knows what is already available in the market to solve a certain problem.

Simon likes sports and he often goes to the gym opposite his house when he has some spare time. As well, he really likes to be in his small office at home, reading or listening to music while having a coffee or tea. He has a large bookshelf with books about a wide range of topics, he is a really curious person. Once a month, he tries to have a weekend trip with this wife to visit a nearby area, hiking around some nice park or visiting a city around Europe well-connected with Bristol airport.

He loves technology, one of the main reasons why he enjoys his current job so much and dedicates himself to it. While commuting to work, he saw an advertisement about a new robot companion recently launched with a quite affordable price. Simon had never thought about acquiring one in the near future, but as technology is progressing so quickly, robot companions have got into the market at a quite reasonable price for the features that they are currently offering. It will be the perfect tool to connect all devices around his house, e.g. music system, television, appliances and so on, and help him to transport some objects from one place to another using the voice command integrated feature.

Simon is looking forward to getting his new gadget, but he will still need to wait a month to receive it at home. He has been reading about the robot features and he is quite happy with the fact that the robot is configurable and its behaviours can be modified between a few options. He would hate to have a robot trying to disturb him from time to time without this being asked before. The distance kept by the companion is adjustable as well, in case he feels the robot gets too close to him during the interaction. This new model seems the perfect tool for him to be immersed in the new era of technology. Simon's main goals using the robot companions could be summarised as follows:

- Enjoying using the robot for browsing, listening to music and reminding of tasks.
- Using the robot to transport objects from one place to the other inside the house.
- Using the robot as a friendly tool whose services can be requested when needed.
- Using the latest technologies and gadgets available in the market, including robots.

6.5.2 The Second Model Approach

Guided by the introduction of a third persona into system and the results from the previous experiment, the initial behaviour model (section 4.3.1), was modified prior to this experiment, see Table 6.1. This time it was was possible to verify the initial assumption through the *Experiment 2* outcomes. For instance, the results suggested that the *Advance Interface* and *Assistance Level* displayed by the robot should remain the same across all users as these options were preferred by the majority of participants in the previous experiment. Also, the *Robot Voice* was also left enabled as this was majority selected in the *Experiment 2*. The rest of robot features will be combined to represent behaviour that could be expected by the three personas that constitute the behaviour model. It is quite important to look for different behaviours based on the well differentiated personas defined. This will help the user to understand the scenario presented and avoid misinterpretations of the robot behaviours during the interaction.

The personas Jessica and Matthew included different proxemics and expressiveness setting as in the initial definition of the model, see section 4.3.1. Regarding the robot proactiveness, the majority of users preferred the "High" condition level, however the new persona, Simon, is created on the basis of users preferring a less proactive robot while keeping other features as defined for Jessica.

Simon is as an adult, extrovert, an expert in technologies and looking for new gadget to incorporate in his house. He is expecting a quite predictable robot that can be highly configurable to avoid this to interrupt at certain times of the day or during certain task at home. Based on this definition, proxemics and proactiveness features are defined as "Low" while the expressiveness is kept "High", similarly to Jessica.

This new version of the model based on the outcomes presented at the previous lines has been depicted in the Table 6.1. This model will be tested and evolved based on the outcomes from the *Experiment 3*.

6.6 Experiment

6.6.1 Experiment Setup

In the previous chapters, see Chapter 3 and Chapter 5, two different studies, *Experiment 1* and *Experiment 3*, were performed to understand people's preferences living

Robot Feature	Conditions	Jessica (Scenario 1)	Simon (Scenario 2)	Matthew (Scenario 3)
Communication	Advance Interface	X	X	X
	Simple Interface			
	Robot's Voice	X	X	X
Proxemics	Personal Zone	X		
	Social Zone		X	X
Assistance Level	High	X	X	X
	Low			
Expressiveness	High	X	X	
	Low			X
Proactiveness	High	X		X
	Low		X	

Table 6.1: Second approach to the behavioural model - Each of the three scenarios and robot behaviours shown during the first session.

in a smart home and people's preferences during the interaction with a robot companion in that environment, respectively. This allowed to gain a greater knowledge of the system in order to think about better ways of adapting robot companions to users' preferences at home. The definition of the *Experiment 3* was based on findings from these previous experiences as part of the iterative methodology followed. A new persona was created on the system, as suggested by the results, and certain robot features were modified and others were considered invariant across the personas already defined in the initial behaviour model. The UH Robot House was again the naturalistic environment used to carry out the research together with Sunflower robot companion (see Section 5.5.1).

During this experiment, the participants were requested to perform the same scenario with Sunflower three different times, one per each persona defined in the new version of the behaviour model. The robot behaviours were modified in accordance with the persona adopted for each scenario, i.e. the robot was behaving as suggested by the model for each of the pre-defined personas. All users were requested to act as they were in their own house and in a natural way as they were not evaluated. Each of the scenarios was recorded during their whole duration and the participants gave their written consent at the beginning of the experiment. The figure 6.3 represents experimental area and the cameras location during performance of the three scenarios:

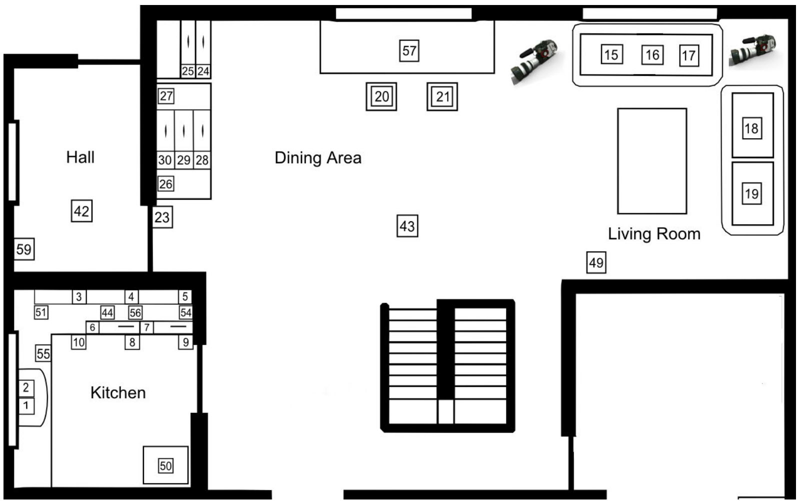

Figure 6.3: UH Robot House map representing the experimental area, ARS sensors' location and cameras' position.

Two sessions were required to complete the *Experiment 3* instead of just one, and these were performed in two different days to give participants time to think about the interaction with Sunflower. The number of days between the first and the second session was never greater of two for any the participants. The participants were informed that the first session would last one hour approximately, and the second session would last around 25 minutes and involve just a questionnaire without any interaction with the robot. As described and approved under Ethics protocol number a1213-13(2), participants were told, after finishing the first session, that they would receive ten pounds at the end of the second session in compensation for their time and effort performing the experiment and coming to the UH Robot House. It is already known about the difficulties of recruiting participants for HRI studies, even harder if they need to perform two different sessions. Therefore, this compensation was found fair as well as rewarding for them. Their participation was entirely voluntary and, at any point during the experiment, they were able to withdraw and terminate the experiment if they felt uncomfortable or just wished to do so. This study involved the collection of video material that was required for the post-experiment analysis. All data gathered on individual participants were treated with full confidentiality, and at no time throughout the whole course of the research project participants names were disclosed, just the anonymous user ID code formed the basis of the evaluations.

The first session began with a brief introduction about the companion capabilities and the house facilities in order to familiarise the user with the environment, see Appendix C.3, similarly to the previous experiment. Before the briefing, the users completed the pre-experiment questionnaire, see section 4.2.3, using the computer. Three new questions were added to the end of the previous pre-experiment questionnaire in order to collect more data about users' thoughts prior to the experiment. Some interesting results were obtained in the previous study regarding the *Approach Distance* variable, where the distance preferred prior to the interaction was correlated to the distance selected after the interaction with the robot companion. Therefore, three new questions that were added to the questionnaire are as follows:

1. Which level of expressiveness would you prefer the robot to have during the

interaction?

2. Which level of proactiveness would you prefer the robot to have during the interaction?

3. Could you indicate the degree in which you would accept the robot to interrupt you during your activities of daily living?

Immediately after filling in this questionnaire, they started to perform the three different scenarios defined for this experiment, see section 6.6.3. These scenarios were presented in a random order (*counterbalancing*) to avoid order effect issue in the repeated measures experimental design. After completion of each scenario, the users needed to fill in a few questions about how comfortable they felt with the robots during the interaction. This procedure was performed two more times, changing the robot behaviour as appropriate. The first session finished after filling a short post-experiment questionnaire where they indicated their preferred scenario of the three that were presented. For further details about the questionnaires see Appendix C.6.

During the second session, the users did not interact with the robot, they just completed the *Second Session Questionnaire*. Users reviewed the robot behaviours presented to them during the previous experiment and using the videos previously recorded. The main researcher was with the participants during the whole second session. After watching each of the scenarios performed during the first session, the participants re-evaluated the robot behaviours observed and rated them using the post-experiment questionnaire. The main idea behind dividing the *Experiment 3* into two sessions was to compare participants' answers during the first session to participants' answers during this second session. Users were given the opportunity of reviewing their interaction and the robot behaviours presented during the previous session in order to better understand the robot features that were displayed during the study. This was a method to verify that their preferred scenario, over the three presented, was still rated as the most suitable for them after visualising again the robot features that were evaluated in the first session. In addition, the method could help mitigate external factors, as learnt from the previous personas experiment, by ensuring that each user selected the most suitable scenario based on their preferences and having a good understanding of the robot capabilities for each of the tasks performed. The second session was concluded after the questionnaire was fully completed.

6.6.2 Participants

A total of 35 participants (18 females and 17 males) took part in the *Experiment 3* carried out at UH Robot House. The participants were briefly introduced to the house facilities and the robot's capabilities before starting the experiment by the main researcher. The participants were asked to perform as if they were in their own house during the experiment, trying to make them feel as comfortable as possible. They were allowed to use any of the resources located in the UH Robot House if they felt like it, so no particular restrictions were made. Each participant performed individually the same scenario three different times, each of the scenarios was presented to all users in a random manner to avoid results bias caused by the order in which they were presented. The demographic data has been summarised in the following table (see Table 6.2):

Participants were recruited from the local area and the University of Hertfordshire. There was not particularly interested in any gender or age-related differences

Variables	Value	N(35)	Percentage
Gender	Male	17	49%
	Female	18	51%
Age	Under 30	17	48%
	30-45	15	43%
	46-60	3	9%
Background	Technology Related	13	37%
	Non Technology Related	22	63%
Previous Experience with Robots	None	21	60%
	Rarely	9	26%
	Occasionally	5	14%
	Expert	0	0%
Number of Hours Using the Computer per Day	Less or equal to 8 hrs	10	29%
	More than 8 hrs	25	71%

Table 6.2: Summary Table - Demographic data from our sample (N=35) in the *Experiment 3*.

when interacting with companions, however, the sample was attempted to be as even as possible. The sample was a mixture of ages, genders and technical backgrounds without following any particular pattern. Given the current exposure to technologies during our daily lives (e.g. using the computer at work or home), the *Number of Hours Using the Computer/Technology per Day* category was divided into just two different values, less or equal to eight hours or more than eight hours, as depicted in the demographic data table presented (see Table 6.2).

6.6.3 Scenarios Definition

As stated before, three different scenarios have been designed for this experiment. Each one is associated with one of the personas defined in the system. Participants needed to complete a pre-experiment questionnaire before performing these scenarios. The data collected has been used to analyse and determine the common users' characteristics among users preferring the same robot behaviours. In this way, it will be possible to match users and personas, so that the computational behaviour model could be defined and robot behaviours adapted to participants during the first interaction with robot companions. Following the initial hypothesis, it is expected to find common characteristics between the users selecting the same preferred scenarios at the end of the experiment. Two sessions were established in order to help understand reasons why this assumption could succeed or fail depending on the outcomes. The second session was defined to verify users' first session answers against this second session answers after the problem detected during the previous study to explain certain outcomes of the study. Finding the set of variables to use to associate personas and users has been the main difficulty found in this approach so far. The experiment outcomes will determine the degree to in which the initial hypothesis can be fulfilled, and how users perceived the sets of robot behaviours defined.

Regarding the scenarios defined, all are based on the same contextual information. The user is at home watching the television, or reading a book in the sofa area. Shortly after the start of the scenario, the robot advises the user to have a drink in order to start the interaction with the participant. As previously mentioned, the robot's communication features and the robot's assistance level were fixed throughout all the scenarios. In addition, the robot LED panel, situated on top of the robot torso, will be configured to blink yellow when moving as a common feature presented across all scenarios. Once the robot reaches its destination, the LED panel will be set to green or another selected colour. The users were always given total freedom to interact as they wished with the companion, but keeping themselves inside the designated scenario area. The scenario described above illustrates the expected interaction when the user accepts the robot's request. At any time the user was free to stop the interaction by rejecting the companion's offers. The following are the definitions of the three scenarios created for the *Experiment 3*:

6.6.3.1 Scenario Guided by the First Persona: Jessica

The user is sitting in the sofa area watching the television, reading or using the mobile phone when the robot approaches at a *personal distance* to the sofa. Once the robot is located at the designated position, it starts *flashing its upper-torso LEDs and moving its head and torso* from left to right in order to catch the user's attention. The robot reminds the user about having a drink, and it just displays the option to go to the kitchen. The user accepts the request and they both go towards the kitchen. The robot goes towards the kitchen flashing its yellow light and it will stop at the kitchen entrance keeping a *personal distance* from the user. Once it is located, the robot starts the same behaviour trying to catch the user's attention again. The robot *offers to transport a drink* back to the living room and opens its tray for the user to place the drink on it. The user opens the fridge, takes a beverage and places it over the robot's tray. Then, the user sends the robot back to the living room, and they both return to the sofa area. The robot stops at a *personal distance* from the user in the sofa area and, after the user picks the bottle from the tray, the robot hopes the user will enjoy his drink. Following this action, the doorbell rings and the robot companion starts *flashing its upper-torso LEDs and moving its head and torso* from left to right in order to catch the user's attention. The robot advises the user that someone could be at the door waiting, and it *goes towards the hall without user's confirmation* but asking the user to follow him. The user checks the front door, collects a parcel and the companion *offers its tray to transport any object* towards the living room after trying to catch the user's attention with *its lights and head and torso movements*. The user accepts the robot's request and they both return to the living room. The robot stops at a *personal distance*, the user picks up the parcel and the scenario gets concluded. An example of the message displayed on the robot's interface can be found in Figure 6.4. The following robot feature conditions have been adopted to perform this scenario:

- *Communication*: Advanced Interface and Voice (Default)
- *Approach Distance*: Personal
- *Expressiveness*: High
- *Assistance*: High (Default)
- *Proactiveness*: High

Figure 6.4: Example of the Robot Interface during the High Assistance Level condition.

6.6.3.2 Scenario Guided by the Second Persona: Simon

The user is sitting in the sofa area watching the television, reading or using the mobile phone. After a few seconds, the robot *starts flashing its upper-torso LEDs and moving its head and torso* from left to right in order to catch the user's attention, however, this action is done *from the robot's home position* to avoid disturbing the user. The companion *suggests to the user to have a drink* and go to the kitchen together. If the user accepts the suggestion, they both go to the kitchen and the user opens the fridge in order to take a beverage. The robot goes towards the kitchen entrance, flashing its yellow LEDs as a sign of movement still in progress. Once the robot is located at the kitchen entrance and at a *social distance*, it tries to catch the user's attention again using its lights, head and torso movements. The robot *offers to transport a drink back to the living room* and opens its tray for the user to place a drink. Once the user takes the drink and leaves it over the tray, the robot's request is accepted and the robot goes back towards the living room together with the user. The robot stops at a *social distance* from the user in the sofa area and hopes the user will enjoy his drink after picking the bottle up from its tray. Following this action, the doorbell rings and the robot companion starts *flashing its upper-torso LEDs and moving its head and torso* from left to right in order to catch the user's attention. The robot advises the user that someone could be at the door waiting, and it *asks for confirmation before going towards the hall.* The user accepts the robot's request and they both go towards the hall. The user checks the front door, collects a parcel and the companion *offers its tray to transport any object* towards the living room after trying to catch the user's attention with *its lights and head and torso movements.* The user accepts the robot's request and they both return to the living room. The robot stops at a *social distance*, the user picks up the parcel and the scenario gets concluded. An example of the message displayed on the robot's interface can be found in Figure 6.5. The following robot feature conditions have been adopted to perform this scenario:

- *Communication*: Advanced Interface and Voice (Default)
- *Approach Distance*: Social
- *Expressiveness*: High
- *Assistance*: High (Default)
- *Proactiveness*: Low

Figure 6.5: Example of the Robot Interface during the Low Proactiveness Level condition.

6.6.3.3 Scenario guided by the Third Persona: Matthew

The user is sitting in the sofa area watching the television, reading or using the mobile phone when the robot approaches at a *social distance* to the sofa. Once the robot is located in the position designated, it reminds the user to have a drink and suggests to go to the kitchen together, in this case, the robot *avoids to catch the user's attention* during the interaction. The user accepts the request and they both go towards the kitchen. The robot flashes its navigation yellow lights while moving until it is located at a *social distance* from the user in the kitchen entrance. The robot *offers to transport a drink back to the living room* and opens its tray for the user to place the drink. The user opens the fridge, takes a beverage, and places it over the robot's tray. The user sends the robot back to the living room and this stops at a *social distance* from the user around the sofa area. Eventually, after the user picks the bottle from its tray, the robot hopes the user will enjoy his drink. Following this action, the doorbell rings and the robot companion advises the user that someone could be at the door waiting, and it *goes towards the hall without user's confirmation* but asking the user to follow him. The user checks the front door, collects a parcel and the companion *offers its tray to transport any object* towards the living room. The user accepts the robot's request and they both return to the living room. The robot stops at a *social distance*, the user picks up the parcel and the scenario gets concluded. An example of the message displayed on the robot's interface can be found in Figure 6.6. The following robot feature conditions have been adopted to run the scenario:

- *Communication*: Advanced Interface and Voice (Default)
- *Approach Distance*: Social
- *Expressiveness*: Low
- *Assistance*: High (Default)
- *Proactiveness*: High

Figure 6.6: Example of the Robot Interface during the High Proactiveness Level condition.

6.7 Results and Analysis

As described in the previous section, a total of 35 participants, see demographic table 6.2, were recruited to perform this experiment where further data were collected to investigate users' preferences regarding the scenarios presented during the trial. Each participant was exposed to the three different scenarios in a random order and following a within-subject experimental design. Therefore, the data were analysed using repeated-measures statistical methods (Field 2013). All the statistics tests were conducted with a 95% confidence level. The main objective was to identify the common users' characteristics from those selecting the same preferred scenarios. The outcomes will help to further define the model and to understand the challenges of the novel approach being investigated. The analysis was divided into three categories, robot features and scenarios, user preferences over these robot features and, finally, users' characteristics and their correlation with the robot features to be evaluated. The experiment data can be found in the Tables 6.3 and 6.4 plus the GitHub repository (*Experiment 3 - User Data - GitHub* 2016) for the users responses to the initial questionnaire.

User	P1-E	P1-P	P1-A	P1-D	P2-E	P2-P	P2-A	P2-D	P3-E	P3-P	P3-A	P3-D
User01	3	3	3	4	1	3	3	5	1	3	3	5
User02	3	3	3	2	2	3	2	4	3	3	3	4
User03	3	3	3	3	1	1	1	5	3	3	1	4
User04	2	2	3	4	1	1	3	5	3	3	3	4
User05	3	3	3	3	3	2	3	4	1	3	3	3
User06	3	3	1	3	3	1	3	5	3	3	1	4
User07	3	3	3	3	3	3	3	4	1	3	3	3
User08	3	3	3	3	3	3	3	5	3	3	3	4
User09	3	2	2	3	3	2	2	3	3	3	2	3
User10	3	3	3	3	3	3	3	4	3	2	3	3
User11	3	3	3	3	3	3	3	4	1	3	3	3
User12	3	3	3	3	3	2	3	4	3	1	3	4
User13	3	1	1	2	3	3	3	3	3	3	3	3
User14	3	3	3	3	1	1	3	3	3	3	3	3
User15	3	3	3	3	3	3	3	4	1	3	3	4
User16	3	2	3	4	2	1	2	4	2	1	2	4
User17	2	1	3	3	3	1	3	4	1	3	3	4
User18	3	1	3	3	3	1	3	4	3	3	3	4
User19	1	1	3	3	1	1	3	4	1	1	3	3
User20	3	3	3	3	2	2	3	4	3	3	3	3
User21	3	3	3	4	3	3	3	4	3	3	3	3
User22	3	3	3	4	3	3	3	5	3	3	3	4
User23	3	3	3	2	3	3	3	3	3	3	3	3
User24	3	3	3	2	3	3	3	3	1	3	2	4
User25	3	3	3	4	3	3	3	4	3	3	3	4
User26	3	3	3	4	3	3	3	4	3	3	3	5
User27	2	2	3	2	2	2	3	4	3	2	3	3
User28	3	3	3	3	3	3	3	4	1	3	3	5
User29	3	3	3	3	3	3	3	3	2	3	3	4
User30	3	3	3	4	3	3	3	5	3	3	3	4
User31	3	3	2	4	3	3	3	5	3	2	3	4
User32	3	3	3	3	3	1	3	4	3	3	3	4
User33	3	3	3	4	2	3	3	4	3	3	3	4
User34	3	3	3	3	3	1	3	4	3	3	3	4
User35	1	3	1	3	1	1	1	3	3	3	1	3

Table 6.3: Users responses to the P1, P2 and P3 scenarios. E:Expressiveness, P:Proactiveness, A:Assistance and D:Distance.

User	S1-E	S1-P	S1-A	S1-D	S2-E	S2-P	S2-A	S2-D
User01	2	2	2	1	2	2	2	1
User02	2	2	2	2	2	2	2	2
User03	2	2	2	1	2	2	2	1
User04	1	2	2	1	2	2	2	1
User05	2	2	2	1	2	2	2	1
User06	2	1	2	2	2	1	2	2
User07	2	1	2	2	2	1	2	2
User08	2	2	2	1	2	1	2	1
User09	2	2	2	1	1	2	2	1
User10	2	2	1	1	1	2	2	1
User11	2	2	2	1	2	2	2	1
User12	2	2	2	1	2	2	2	1
User13	1	2	2	2	1	2	2	2
User14	2	1	2	2	2	1	2	2
User15	2	1	2	1	2	1	2	1
User16	1	2	2	1	1	2	2	1
User17	2	2	1	1	2	2	1	1
User18	2	1	2	1	1	1	2	1
User19	1	1	1	2	1	2	2	2
User20	2	1	1	2	1	2	2	1
User21	1	2	2	1	1	2	2	2
User22	2	2	2	1	2	2	2	1
User23	2	1	2	1	2	1	2	1
User24	2	1	2	1	1	1	2	1
User25	2	2	2	1	2	2	2	1
User26	2	2	2	1	2	2	2	1
User27	2	2	2	1	1	2	2	1
User28	2	2	2	2	2	2	2	1
User29	1	1	2	1	1	1	2	1
User30	2	1	2	1	2	1	2	1
User31	2	1	2	1	2	2	2	1
User32	2	1	2	1	2	1	2	1
User33	2	2	2	1	2	2	2	1
User34	2	1	2	1	1	2	2	1
User35	2	1	2	2	2	1	2	2

Table 6.4: Users responses to the preferred robot features after the first session (S1) and the second session (S2). E:Expressiveness, P:Proactiveness, A:Assistance and D:Distance.

6.7.1 Robot Features and Scenarios

6.7.1.1 First Session - Robot Features

In this first session, the participants were asked to interact with the robot through a set of tasks defined during the scenario and, immediately after finishing this scenario, in order to rate each of the robot's features presented during the interaction. Based on the analysis of data, it was observed that the *Proactiveness* feature was found significantly different between scenarios, in the cases where a different condition was actually presented. The Wilcoxon signed-rank test calculated for each feature-scenario combination was represented in figure 6.5. This result matches the new definition of the computational behaviour model, redefined during this experiment. On the other hand, the *Approach Distance* and *Expressiveness* features were found significantly different between the scenarios, but not for all the scenarios expected. The *Scenario 2* and *Scenario 3* of the *Approach Distance* feature was seen as different by users but the distance was kept exactly the same between both scenarios. The same sort of unexpected result was obtained for the pairs *Scenario 1-Scenarios 2* and *Scenario 2-Scenarios 3* of the *Expressiveness* feature, which were seen as different and equal, respectively, but the result for those should have been the opposite. Based on these results, it seems that users could have been evaluated the expressiveness based on the approach distance, however, the *Approach Distance* and *Expressiveness* were not found correlated when evaluated on each individual scenario. Finally, it is worth to mention that the *Assistance Leves* was not found statistically significant for any of the scenarios as it was always presented in the same way to participants.

Based on the data, it seems that users did not apprehend a clear difference

Robot Feature	Scenario	Z	Sig.(2-tailed)	Actual Difference
Approach Distance	Scenario1 vs. Scenario2	-4.7675	0.000*	Yes
	Scenario2 vs. Scenario3	-2.524	0.012*	No
	Scenario3 vs. Scenario1	-3.750	0.000*	Yes
Expressiveness	Scenario1 vs. Scenario2	-2.165	0.030*	No
	Scenario2 vs. Scenario3	-0.745	0.456	Yes
	Scenario3 vs. Scenario1	-2.166	0.030*	Yes
Assistance Level	Scenario1 vs. Scenario2	0.000	1.0	No
	Scenario2 vs. Scenario3	-0.378	0.705	No
	Scenario3 vs. Scenario1	-0.276	0.783	No
Proactiveness	Scenario1 vs. Scenario2	-2.425	0.015*	Yes
	Scenario2 vs. Scenario3	-2.904	0.004*	Yes
	Scenario3 vs. Scenario1	-0.730	0.465	No

Table 6.5: Wilcoxon Signed-Rank Test Values for each Robot Feature Evaluated During the First Session (* Statistically Significant $p<0.05$).

between certain robot features during the performance of the experiment. The following chart represents the uniformity of the robot features evaluated after performing each scenario, see Figure 6.7. However, during the second session users were able to distinguish all robot features differences after analysing the video for each of the scenarios performed, see Section 6.7.1.2. To further investigate the cause of these interesting results, the users' explanations during session 2 were reviewed in order to understand for the variations found in their rating. After watching the videos participants rated the same robot features differently compared to the responses during the interaction. The *Expressiveness* and *Approach Distance* were the main features to compare as their results differ from the expected data during the evaluation of the first session.

Regarding the *Expressiveness*, several users stated that the lack of experience in similar experiments made them see the robot's expressiveness as high between all scenarios. The robot approaching and initiating the conversation was already sufficient for their initial expectations. Users with *None* robot experience tended to rate the robot's features quite similarly across the different scenarios presented when compared to users with *Rarely* or *Occasional* robot experience, however, no significant correlations were found to support this trend. Other users, for instance, were so focused on the voice and the task itself that they were not paying attention to the head movements or robot's lights, so they were not able to appreciate these changes. In terms of the *Approach Distance* feature, some people saw all distances as the same between scenarios, or the distance got increased, or decreased, depending on how they located themselves in the sofa during the scenario. Other users stated that the social distance was still seen as *High*, or they had the feeling that the robot was closer during the interaction compared to what they later realised when they watched the videos. As it can be observed, there are too many external factors that could make the evaluation process highly complex in HRI studies, even more difficult when trying to model users' expectations and preferences for companions. It was a great benefit to have a second session to check users' interpretations and re-evaluate the robot's features from a different point of view, as it was designed for this experiment after experience gained from the previous one.

After performing the three scenarios, the users completed the post-experiment questionnaire in order to collect some more data. Users were briefly asked about the differences that they saw and their preferred scenario in retrospect from the three presented during the first session. As the *Robot Interface* and the *Verbal Communication* robot features were presented as a default condition, based on the findings from the previous experiment, the questionnaire included a few more questions to get an overall idea about how these features were observed. The *Advance Interface*

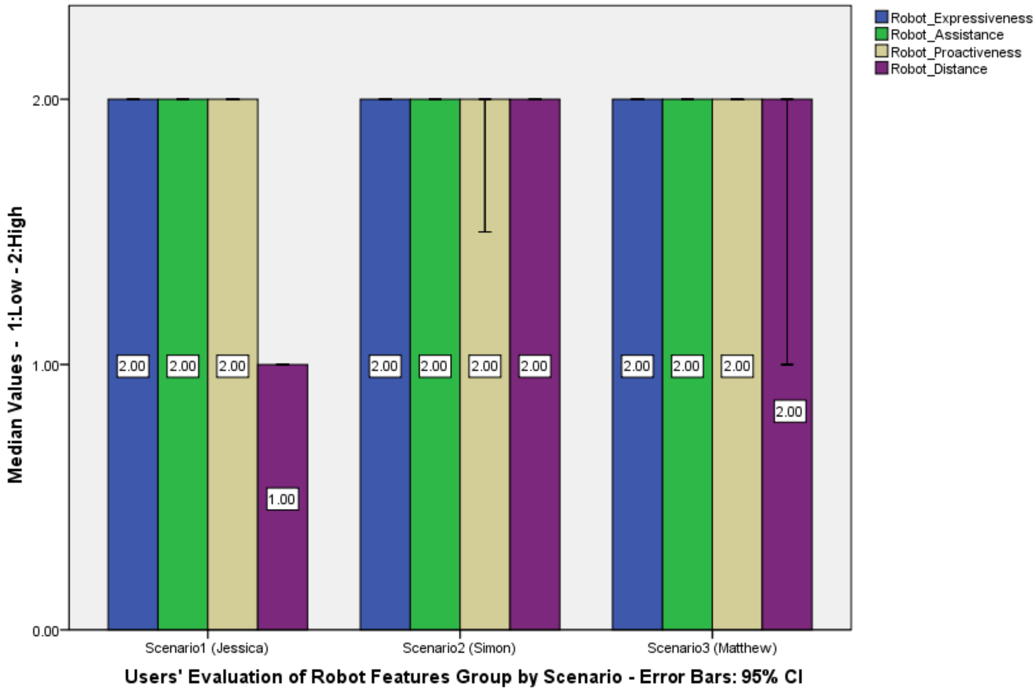

Figure 6.7: Users' evaluation of the robot features presented during the first session (1:Low - 2:High).

defined was found quite acceptable by the majority of users, a frequency chart has been depicted in figure 6.8. The 88.6% of the participants stated that they will *not modify the interface at any point during the interaction*. In the same way, the robot's voice was evaluated and 85.7% of users replied positively to the idea of *leaving the voice-activated during the experiment*. One of the main negative comments was the voice tone used in the robot companion. This should be considered in future experiments and a configurable voice tone option could be introduced.

6.7.1.2 Second Session - Robot Features

During this second session, users had the opportunity of observing, by watching the videos of the previous session recorded, the three different scenarios and evaluating

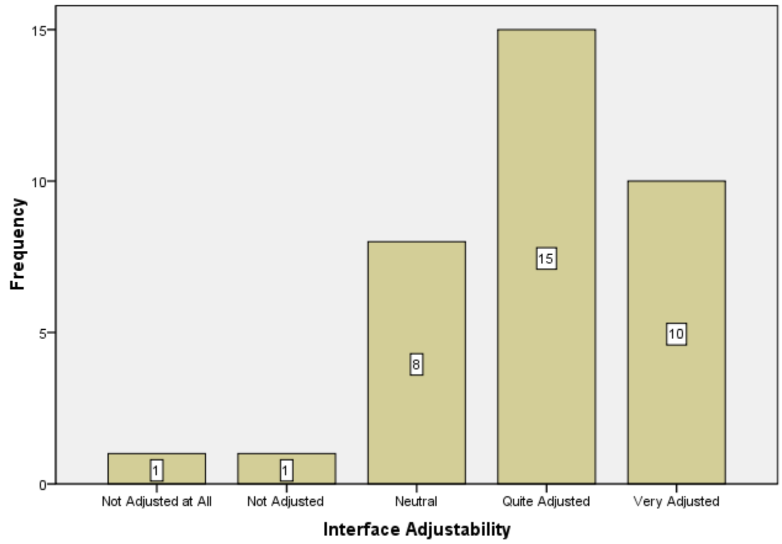

Figure 6.8: User's Rating Frequencies for the Robot Interface Shown During the Experiment.

the robot features shown in each of those scenarios. The Wilcoxon signed-rank test was conducted on the data collected after this evaluation, in the same way that it was performed during the first session. On this occasion, the results show that the two conditions, *Low* and *High*, presented for each robot's feature, were perceived as significantly different between scenarios when the behaviour was actually modified (see Table 6.6). The obtained results nicely represent the model proposed, see table 6.1, for this *Experiment 3*, which indicates the success of users correctly identifying the robot conditions defined, but this only happened after the analysis of the videos in the second session. Compared to the previous experiment, *Experiment 2*, where each robot's feature-condition was individually presented to the participants at the time, this experiment could have included too many details to be evaluated at the same time, so that users were not always able to understand and process all the information. This comes back to the previous discussion in section 4.2.1, where it was stated the difficulties of designing well differentiated behaviours to achieve the expected evaluation from users, otherwise, they could end up not appreciating the differences between robot's performances.

Robot Feature	Scenario	Z	Sig.(2-tailed)	Actual Difference
Approach Distance	Scenario1 vs. Scenario2	-5.396	0.000*	Yes
	Scenario2 vs. Scenario3	-0.378	0.705	No
	Scenario3 vs. Scenario1	-5.657	0.000*	Yes
Expressiveness	Scenario1 vs. Scenario2	0.000	1.000	No
	Scenario2 vs. Scenario3	-5.745	0.000*	Yes
	Scenario3 vs. Scenario1	-5.745	0.000*	Yes
Assistance Level	Scenario1 vs. Scenario2	-1.000	0.317	No
	Scenario2 vs. Scenario3	-1.342	0.180	No
	Scenario3 vs. Scenario1	-1.633	0.102	No
Proactiveness	Scenario1 vs. Scenario2	-5.145	0.000*	Yes
	Scenario2 vs. Scenario3	-5.396	0.000*	Yes
	Scenario3 vs. Scenario1	-1.000	0.317	No

Table 6.6: Wilcoxon Signed-Rank Test Values for each Robot Feature Evaluated During the Second Session (* Statistically Significant - $p<0.05$).

As it can be observed in the figure 6.9, the variation found during the first session, and the incorrect identification of some of the robot's feature-conditions, was corrected and the features were correctly identified after the video analysis in the second experiment session. Users were able to determine the behaviours that implemented into the robot companion for each of the three scenarios performed. This positively contributed to create a better picture of the system inside the user regarding the different behaviours that the companion could adopt during the interaction, and make them think about the combination of those to define their first interaction with a robot companion at home. The second session questionnaire included the option to modify the preferred scenario selected in the first session and re-evaluate each of the robot's features shown during the experiment. The results about user preferences for the study are discussed in the following section.

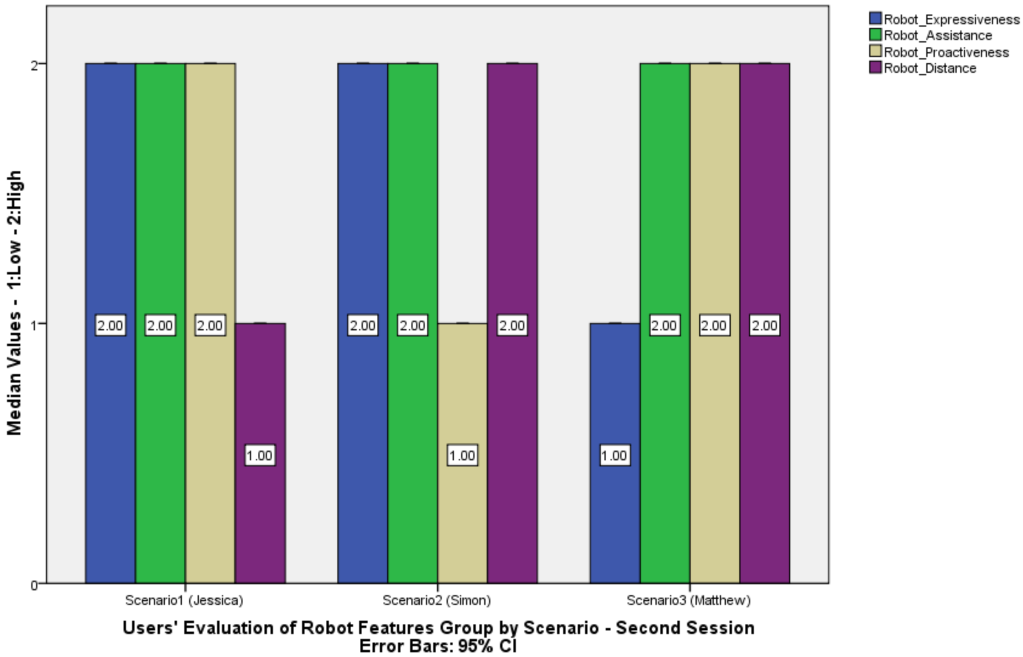

Figure 6.9: Users' evaluation of the robot features during the second session and after examining the videos of the scenarios performed (1:Low - 2:High).

6.7.2 User's Scenario Preference

6.7.2.1 First Session - Scenario Preference

The user's preferred scenario, meaning the persona that could better match their preferences when interacting with a companion, was one of the targets to achieve during this experiment. Based on the values selected by users, the distribution of participants selecting which scenarios they preferred during the first and the second sessions was represented in table 6.7. A positive significant correlation was found between the selections made in the first scenario and the second session for each of the robot features evaluated ($r(35)=0.891$, $p=0.000$). It could be observed how users' preferences have been distributed across the scenarios shown, being the Scenario 1 (*Jessica*) the most popular among users. This result matches the outcomes from the *Experiment 2*, where the highest of the conditions for each robot's feature was generally preferred by users. As the result was obtained again but with a different and bigger sample, it is possible to state that the robot behaviour implemented guided by Jessica, one of the personas of the model, was certainly preferred by the majority of users, so that the main efforts should be focused on finding the differences that make the other scenarios to be selected.

Scenario	Persona	First Session	Second Session	Difference
Scenario 1	Jessica	18 users	20 users	+2
Scenario 2	Simon	9 users	8 users	-1
Scenario 3	Matthew	8 users	7 users	-1

Table 6.7: Users' Preferred Scenario Selection for the First and the Second Session.

After evaluating the robot's features shown during the experiment, users were asked in the post-experiment questionnaire to select their preferred condition for each of the features that the robot was displaying during the interaction, these are *Expressiveness*, *Assistance Level*, *Proactiveness* and *Approach Distance*. Users' preferences were grouped by the scenario selected. This way help to visualise whether these users tend to choose similar conditions as the ones proposed by the computational behaviour model. The robot conditions were selected between *1=Low* and *2=High*, except the *Approach Distance* that was selected between *1=Personal* and

2=Social. The following figure 6.10 represents the values obtained. A Friedman test was conducted to determine whether the results obtained were significantly different among the variables measured. According to the analysis, there is a statistically significant difference perceived in the data ($\tilde{\chi}^2(3) = 32.125$, p=0.000).

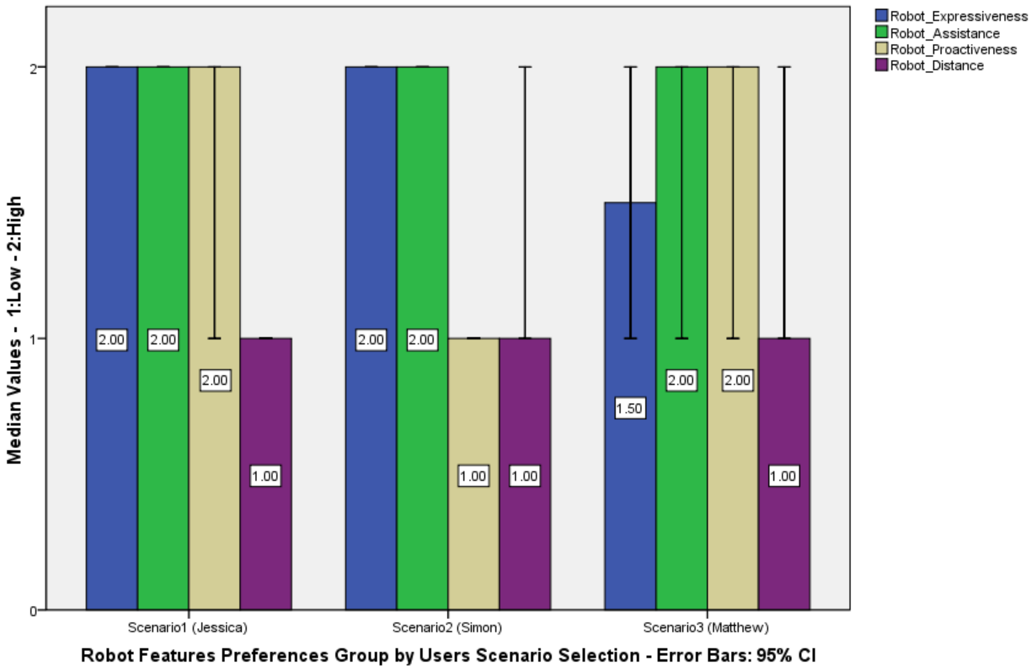

Figure 6.10: Users' preferences for each robot feature grouped by the preferred scenario selected during the first session (1:Low - 2:High).

6.7.2.2 Second Session - Scenario Preference

During the second session, participants had the chance of watching the videos of the experiment performed in the previous session. After evaluating the three scenarios they were asked to select their preferred condition for each of the four robot features shown. As depicted in figure 6.11, the users' preferences of the robot's features, when grouped by users' preferred scenario, are quite similar to the second approach of the behaviour model. Once users were able to identify each behaviour, it seems that the initial definition of the model matched the participants' expectations during the interaction with the robot companion. The fact that users gained a better understanding of the robot features shown and the robot's capabilities, was positively contributing to improve their knowledge about the system. This made users select their preferences accordingly while, based on some users comments, translating themselves to a hypothetical interaction with the companion before selecting the values. As stated in the previous section, the robot conditions were selected between *1=Low* and *2=High*, except the *Distance* that was selected between *1=Personal* and *2=Social*. Also, the Friedman test was conducted to determine whether the results obtained were significantly different between the variables measured. According to the analysis, there is a statistically significant difference perceived in the data ($\tilde{\chi}^2(3)$ = 36.000, p=0.000). In addition, a significant positive correlation was found between the selection made in the first scenario and the second session for each of the robot features evaluated, *Expressiveness* (r(35)=0.470, p=0.004), *Assistance* (r(35)=0.477, p=0.004), *Proactiveness* (r(35)=0.712, p=0.000) and *Approach Distance* (r(35)=0.770, p=0.000).

6.7.3 Users' Characteristics vs. Robot Features

As in *Experiment 2*, users' characteristics and preferences collected through the initial questionnaire were analysed in order to look for correlations between these and the robot's features selected with values *1=Low* and *2=High*. This will be part of the iterative methodology approach in order to determine the set of variables that better explain the selection of certain robot features over others. These variables

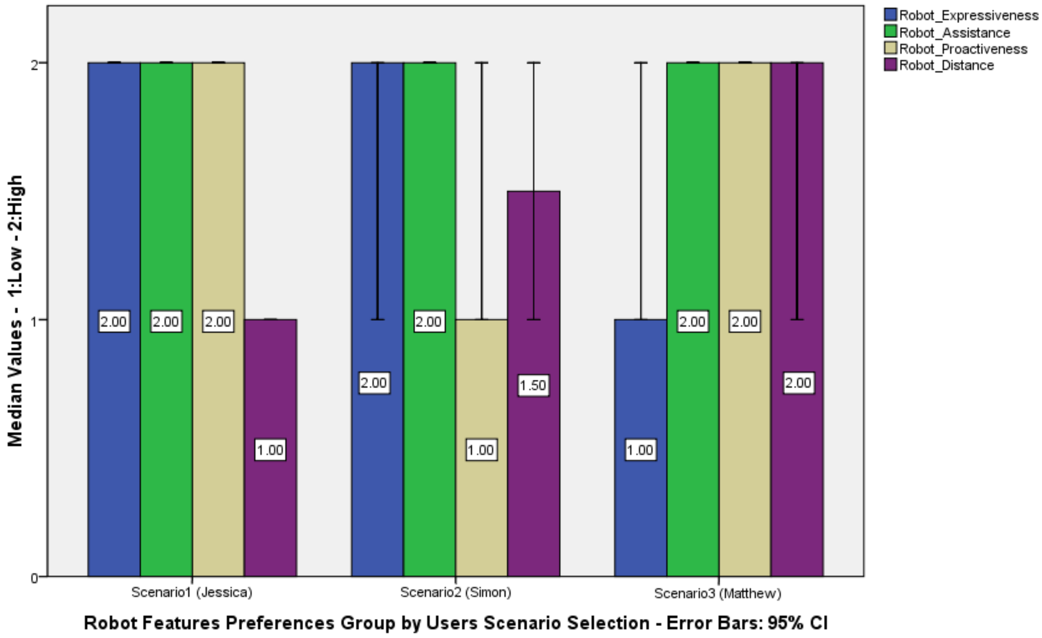

Figure 6.11: Users' preferences for each robot feature grouped by the preferred scenario selected during the second session (1:Low - 2:High).

will be later used to define the match between users and personas based on the model created. The gender and the age were not correlated with the preferred robot features selected by participants, however, and as mentioned before, these characteristics were not particularly interesting for this research purposes.

Personality Traits	Correlation Coefficient	Sig.(2-tailed)
Extroversion	0.824	0.000*
Agreeableness	0.825	0.000*
Conscientiousness	0.715	0.000*
Emotional Stability	0.914	0.000*
Openness	0.883	0.000*

Table 6.8: Spearman's Correlation Coefficient - User Personality traits values for Session 1 and Session 2 (* Statistically Significant - p<0.05).

Regarding the personality test, this was completed during the first and the second session of the experiment and a significant positive correlation between both users' answers was found for each of the personality traits from both questionnaires, see Table 6.8. For the analysis of data, the mean values were used, as suggested in the definition of the TIPI questionnaire (*TIPI - Ten Item Personality Measure* n.d.), to calculate the correlation with other variables when evaluating personality traits. In the same way, and as described above, a significant positive correlation was detected among robot's features selected during the first and the second session, so the values from the second scenario were chosen to evaluate the correlations.

Comparing the users' personality traits with each of the robot features evaluated during the second session, a significant negative correlation was found between the *Approach Distance* and the *Agreeableness* (r(35)=-0.363, p=0.032) and the *Openness* (r(35)=-0.419, p=0.012) personality traits. The correlation is negative as *Personal Distance* was represented with value 1 on the data. This correlation between *Distance* and *Agreeableness* was already obtained in the *Experiment 2*, see Table 5.5, however, the second correlation found, *Openness*, seems an interesting new result to be taken into account and in the same direction that the Takayama et al. findings regarding the *Agreeableness* (Takayama & Pantofaru 2009), as described in Chapter 5.6. In terms of comfortableness variables, *Comfortableness Being Approached by a Robot* (r(35)=-0.361, p=0.033), *Comfortableness when Physically Close to a Robot* (r(35)=-0.354, p=0.037) and *Comfortableness Moving in the Same Room that a Robot* (r(35)=-0.491, p=0.003) were found to have a significant negative correlation with the *Approach Distance* robot's feature evaluated. This result confirms the trend set on the previous experiment between *Personal Distance* and *Comfortableness* variables. Finally, the questions from the pre-experiment questionnaire regarding how users thought that they will prefer the robot to behave were compared to the robot features. It was interestingly found that the *Approach Distance Preferred* (r(35)= 0.418, p=0.012), the *Robot Expressiveness* (r(35)= -0.491, p=0.003) and the *Assistance Median* (r(35)= -0.350, p=0.040) expected prior to the experiment were all significantly correlated with the *Approach Distance* preferred during the interaction with the robot companion. Similar results were obtained in the previous experiment where the *Approach Distance* expected before the experiment was positively correlated to the *Approach Distance* selected during the actual interaction with the companion. Also the *Interruption Level* (r(35)= -0.360, p=0.034) value asked during the questionnaire was found significantly negatively correlated to the *Low Proactiveness* level presented in the *Scenario 2*, which indicates, as in the previous experiment, that participant's thoughts prior to the experiment could be a good indicator of the robot behaviour expected during the interaction. The significant correlations found are summarised in the Table 6.9.

Robot Feature	User Variable	Correlation Coefficient	Sig.(2-tailed)
Approach Distance	Pers. Agreeableness	-0.363	0.032*
	Pers. Openness	-0.419	0.012*
	Comf. Being Approached	-0.361	0.033*
	Comf. Close to Robot	-0.354	0.037*
	Comf. Same Room as Robot	-0.491	0.003*
	Distance Preferred	0.418	0.012*
	Distance Preferred	-0.491	0.003*
	Assistance Median	-0.350	0.040*
Proactiveness (Low)	Interruption Level	-0.360	0.034*

Table 6.9: Spearman's Correlation Coefficient - Significant correlations found between user's variables and robot features. (* Statistically significant variable).

In a different sort of analysis, and after grouping users by preferred scenario and calculating correlations between the variables, a significant correlation was just found for the group of users selecting the Scenario 1 (Jessica), see Table 6.10. The variable *Agreeableness* was found to have a significant positive correlated with the *Robot Expressiveness* (r(20)=0.484, p=0.030). The same sort of significant correlation was found between the variable *Comfortable in the Same Room* and the *Robot Expressiveness* (r(20)=0.500, p=0.025) and the variable *Hours Using Computer/Technology per Day* and the *Robot Expressiveness* (r(20)=0.577, p=0.008). All these results are related to the definition of the Jessica persona, and how more agreeable users, used to technology and comfortable co-habiting with robots will prefer a more expressive robot to interact with them. An interesting result was found during the investigation of the *Interruption Level* variable, which measures how much participants allow a robot companion to interrupt them during their activities of daily living. The variable, collected through the initial questionnaire (see Appendix 4.2.3), was found significantly negatively correlated (r(20)=-0.514, p=0.020) to the *Approach Distance* robot feature, which indicates that users allowing the robot to interrupt more frequently will prefer robots to get closer to them.

Robot Feature	**User Variable**	**Correlation Coefficient**	**Sig.(2-tailed)**
Expressiveness	Pers. Agreeableness	0.484	0.030*
	Comf. Same Room	0.500	0.025*
	Hours Computer/Technology	0.577	0.008*
Approach Distance	Interruption Level	-0.514	0.020*

Table 6.10: Spearman's Correlation Coefficient - Significant correlations found between user's variables and robot features for participants preferring *Scenario1 - Jessica*. (* Statistically significant variable).

6.8 Discussion and Conclusion

During this experiment, the investigation of the personas technique was continued following the iterative methodology described in Chapter 1.4. The outcomes from the previous experiment, see Chapter 5, were analysed and used to modify the model and expand the number of personas prior to this study. The expansion provided a wider combination of robot behaviours during the scenarios described above, see section 6.6.3. The three personas described in the model guided the definition of each of the scenarios and the combination of robot's features that best, based on my knowledge, could represent the needs of the users interacting with this system. The main purpose was to find the participants' preferences when interacting with the robot companion based on the robot behaviours presented. Defining the relation between the users' preferences and the robot behaviours will allow the identification of users' patterns to define the computational behaviour model, so each user could be matched to a persona in order to adapt the robot companion behaviours before the interaction.

A total of 35 participants were exposed to each of the scenarios in a random order and rated their experience during the interaction with the robot intermediately after the scenario was finished. Two sessions were defined for this study, as a result of some difficulties detected during the previous one, where it was not trivial to understand some participant's preferences and extract patterns based on the analysis of the users' characteristics investigated. During this experiment, users were asked to evaluate the scenarios from a different point of view in order to understand their rating during the performed experiments. This second session helped achieve one of the purposes for which this was created, as users rated their preferred scenarios and robot features based on a good understanding of the system and their needs when interacting with a companion. It was observed that users could not always process all the information presented during the study as they could have felt under pressure or exposed to a new experience. This could have affected the way in which users rated the robot's behaviours during the first session, which was found different to the results achieved during the second session of this study. HRI researchers should be aware of the risks of considering user's data collected through questionnaires ground truth and state findings after the evaluation process without evaluating the significance of those or contrasting with a second session. In the author opinion, the data should be carefully interpreted, and when possible, double-checked with users in order to avoid generalising results that could be biased by external factors not considered, or unexpected, during the execution of the HRI studies.

The methodology used allowed the introduction of modifications in the initial definition of the model without changing other modules or component of the system, which facilitated the investigation process. As exposed above, a new persona was defined and introduced into the model in order to expand the combination of robot features that were shown to users during the study. This expansion was expected to help distribute users' preferences across the three scenarios presented in the experiment. After the analysis of results, i observed how the first scenario (*Jessica*) was the most selected with a total of 20 users out the 35 we recruited, it was observed how the second scenarios (*Simon*) got a total of 8 users, and the third scenario (*Matthew)* was preferred by 7 users. According to the results, it could be stated that the definition of the scenarios and the robot behaviours based on the personas created has successfully helped distribute users across the scenarios preferences. The scenario implementing the first persona, Jessica, was expected to score higher as it was suggested in the previous Chapter 5. The results support the *H1* which stated that the expansion of the initial model would improve the classification of users regarding their preferences when interacting with the companion.

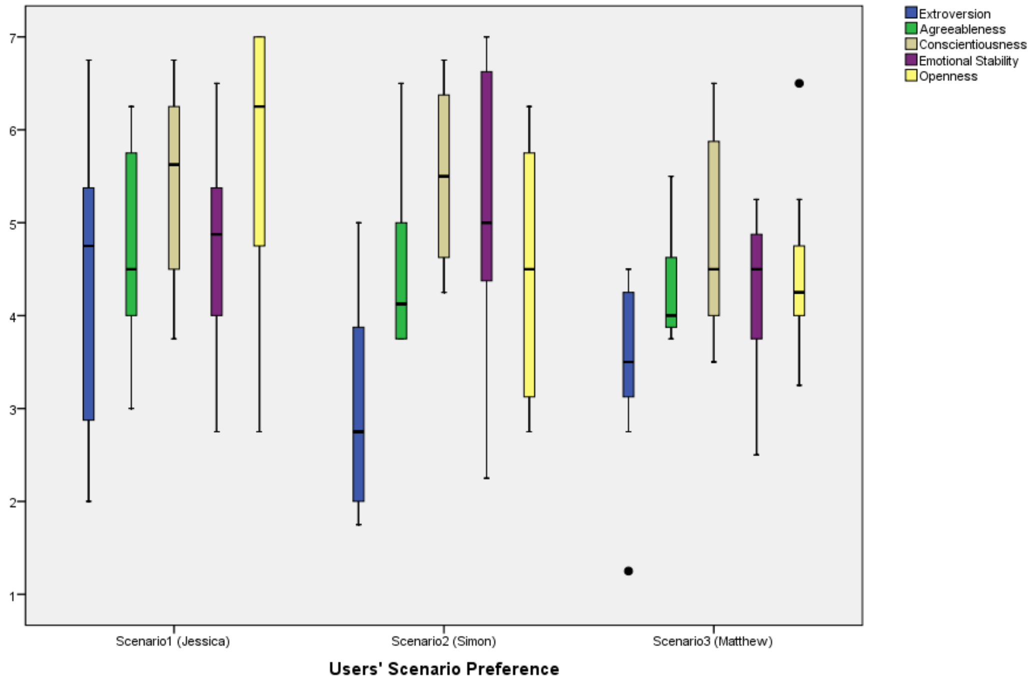

Figure 6.12: Users' personality group by the preferred scenario selected during the second session. The circles in the graph represent the outliers for each variable.

However, as occurred during the *Experiment 2*, it was difficult to find a clear pattern in the pre-experiment variables' values of the participants selecting the same preferred scenarios. Guided by the *RQ3*, the results were analysed looking for a pattern among the users having the same preferences when interacting with a robot companion. However, the second hypothesis *H2* cannot be fully accepted due to the variability of the data when users were grouped by the scenario selected as the most suitable for them. The graph 6.12 represents the personality traits and their mean values for each of the participants selecting the same preferred scenario. As observed, the traits' values are quite similar between scenarios and certain traits' minimum and maximum values are quite distant. In addition, none of these traits' values was shown as normally distributed, which at least could have indicated a tendency within the traits evaluated. One possible reason could be the sample size, but comparing the size of this sample with the one in the previous experiment, but this time the sample size was increased by 75% and similar outcomes were obtained in this regard. These results made difficult to determine patterns in order to define the computational behaviour model targeted.

In order to get a better understanding about difficulties in analysis HRI studies, user' own experience can be presented. During the first session, users were asked about whether they comprehended differences in the robot's behaviour across the three scenarios presented, all participants except one answered positively to this question. This user commented *"In my opinion, the robot performed exactly the same the three times"*. However, the differences appreciated by the majority of users, and the results achieved, were not the expected as it was pointed out during the analysis of data. On the other hand, 92% of the robot features evaluated after watching the videos were correctly recognised by the participants. Inconsistency on the values provided by users during the studies increases the difficulty of analysing the data in the HRI field, and can be considered as one of the difficult factor to identify and explain. In the author's opinion, it is normal that participants felt stressed when exposed to unknown situations, and this should be taken into consideration by researchers in the HRI field. The second session created in this experiment was designed to cope with these inconsistencies and address the problems found during the first experiment.

Regardless the difficulties, it was still possible to identify a set of significant variables to explain users' preferences of certain robot features during the evaluation of the interaction. The definition of the model to be presented at the end of this dissertation, see Chapter 7.2, will be defined by the statistically significant users' variables found during the two studies that were performed in order to evaluate the introduction of the personas technique as part of the computational behaviour model. As it will be presented in the next chapter, each value of the variables forming the model will be calculated from the group of participants who selected the same scenario as their preferred during this study. After the analysis of data, the number of variables to be included in the model can be increased, e.g. *Interruption Level*. Also other variables from the *Experiment 2* confirmed their trends and significance during this experiment, so they will be incorporated into the computational behaviour model definition. This second approach of the computational behaviour model was defined as a combination of knowledge and issues found during the previous experiments performed during this research, see Table 1.1.

The use of the model for the definition of the scenarios and the robot behaviours showed a great result based on the research outcomes. All participants rated one of the three scenarios presented, each one associated with one persona of the initial model, as the most suitable to their preferences and needs. This result can be seen as one of the big advantages of using personas for designing HRI studies. Also, the robot behaviours presented were defined based on the information described for each persona and without directly involving users to specified the behaviours prior to the study. This will help to answer the research question *RQ4* and present to the community the effort in understanding how to investigate the personas technique as part of a computational model for robot companions in HRI studies. The knowledge gained during the performance of this study will help answer this research question in the next chapter, see Chapter 7.3. The answer will be based on the previous lines findings and a mixture of expected and unexpected findings discovered during this investigation.

To summarise, this experiment results show an improvement on the investigation of personas for HRI studies when compared to results from the previous study. The modifications introduced into the system provided the expected results and it helped to get the experiment sample distributed between the different scenarios presented. The analysis of results brought further information about the user's needs interacting with companions, and at the same time, it has emphasised the difficulties of modelling users in HRI studies. A well-defined set of user variables that could certainly explain the relation between the user's preferences and the robot behaviours has not been achieved yet, however, some of the variables found as significant in the previous experiment were confirmed as so during this study. Based on these significant variables found it was possible to define an initial model to be applied to robot companions during the first interaction with the user, but unfortunately, this model should not be generalised based on the limitations of the studies, despite the original expectation of defining a general computational behaviour model for HRI studies. The integration of an HCI technique into an HRI behaviour model could be not as trivial as thought at the beginning. The difficulties predicting the first interaction with robot companions at home plus the lack of extensive data in the field in similar environments make the modelling task quite challenging. However, as it has been pointed out along this document, this research tries to present a new approach and bring a discussion to the HRI field in order to close the gap currently found when performing human-robot experiment in smart homes. This dissertation presents the steps followed during the investigation and exploration of a novel approach and further investigation should emerge from the initial findings.

6.8.1 Experiment Limitations

As per the previous study, *Experiment 2*, the sample did not represent all different age-groups, however, the number of participants for a HRI experiment could be considered medium to large. In addition, this sample was randomly selected but trying to keep the balance in terms of gender, background and previous experience in HRI studies, so the analysis of data and tendencies found should help future investigations in the HRI field. Nevertheless, the outcomes should not be generalised and they should be treated as guidelines when designing HRI studies in smart homes. Researchers in the field are aware of the difficulties of recruiting participants and the need to adapt their studies to the number of participants gathered for each particular experiment.

Based on the results of this experiment, it could be stated that some of the initial assumptions were fully met and others will still need further investigation. For instance, participants were expected to be evenly distributed across the scenarios defined when being asked about their preferred one. The results showed the Scenario1 represented by the persona *Jessica* was the most popular among users with Scenario2 (*Simon*) and Scenario3 (*Matthew*) being evenly distributed as secondary choice. This result was somehow expected based on the *Experiment 2* results as participants tended to select the highest functionality showed by the robot independently of the participant's needs with domestics tasks, however is interesting to see how the other scenarios where evenly selected by the rest of users. This outcome supports the idea of using personas to define the HRI studies as each of the robot behaviours shown per scenario matches the characteristics defined for each pre-defined persona when interacting with a robot companion at home. On the other hand, it was still difficult to find a clear pattern among users selecting the same robot features as preferred, so it is still not possible to predict accurately how this selection was made based on the user characteristics gathered and evaluated for each individual of the sample.

It must be considered the possibility of these results being biased by the experiment procedure selected. Exposing all participants to the three scenarios in a randomly selected order could have created some sort of unexpected outcome very difficult to detect in sample of this size. As well, the way of asking the questions in the experiment forms could be interpreted differently for each participant and it could cause a side-effect that again would have been hard to perceive. Exposing humans to robots and studying their behaviour in each new situation increase the possibility of obtaining unexpected results that must be used as valuable knowledge to move forward in the field of HRI.

It could be concluded that certain problems were addressed and solved during this study, but some of the other issues discovered during the previous experiment still remain unanswered, for instance, the assumption of users preferring the same robot behaviour will have similar characteristics. Future work done over this research approach should focus on the problems pointed out during this dissertation. It will be quite interesting to discover the factor or factors that could explain the results achieved during the *Experiment 2* and *Experiment 3*. Regarding the investigation process and methodology, the outcomes from the previous experiment were taken to analyse and identify the modifications to be integrated into the behaviour model during this second iteration. The results showed that the expansion of the number of personas helped to better identify user preferences when interacting with a companion. However, these results should not be generalised and further investigation will be needed to clarify the issues identified when integrating the personas technique into a computation behaviour model for robot companions.

Chapter 7

Conclusions

7.1 Summary and Conclusion

The main purpose of this research has been the investigation of a novel computational behaviour model for HRI. The model is based on the personas technique presented by Alan Cooper more than a decade ago (Cooper 1999) inside the field of HCI. The integration of this technique into a behavioural model for robot companions, will help to associate users with personas and adapt the robot's behaviours to their characteristics and needs even before the first encounter. The creation of such a model will contribute to reduce the amount of user data that must be collected prior to the first interaction. This data is required to train the system on each robot features studies and get a better understanding of users' needs during the interaction with a robot companion. Therefore, this research and the model proposed try to reduce the burden put on the HRI participants during early stages of the system development once the model is defined. In addition, robot companions are configured with the social capabilities expected by humans, and necessary to improve and engage the interaction between humans and robots. In order to achieve this, a set of experiments were performed, see Table 1.1, to build a system able to integrate and define this behaviour model based on the outcomes of each of the experiments carried out during this investigation.

The first step was to define an initial set of personas and computational behaviour model based on previous studies performed in our research group, see Section 4.2.2 and 4.3.1. Then, an iterative methodology was used throughout this research in order to modify and expand this initial set of personas and the model based on the outcomes obtained after each iteration. The computational behaviour model is responsible for matching each user to one of the pre-defined personas of the system so that the robot behaviour is accordingly adapted to the user's preferences before the first encounter. The UH Robot House, environment used during this research, was lacking a module to detect a user's activities based on the sensors installed around the house. Therefore, the Activity Recognition System was defined to improve the context-awareness of the UH Robot House robot companions during. This system was a vital aspect to address during early stages of the investigation. The creation and evaluation of such a system, see Chapter 3, helped understanding users' preferences when living in the UH Robot House and gave a better insight into the challenges to be faced during the research process.

Two experiments, *Experiment 2* and *Experiment 3*, were conducted at the UH Robot House in order to investigate the computational behaviour model approach described in this dissertation. The first of these two studies, see Chapter 5, involved 20 participants aged between 20 and 40. The main purpose was to determine the variables and the users' characteristics that could be used to define the matching between the user and the initial set of two personas defined in the system. The outcomes helped designing the next study, expanding the number of personas initially designed and modifying the behavioural model, although the initial expectations were not fully met. In the second of these experiments, see Chapter 6, a total of 35 participants, aged between 20 and 60, were recruited to run the experiment in the same location. A complete scenario was defined where users were interacting with the robot companion to perform activities of daily living in the smart home. Users performed the same scenario three times and in a random order. Each scenario was corresponding to one of the three different pre-defined personas and the way in which these define the robot's behaviour for each of the tasks presented during the scenario. The reduction of variables after the first iteration helped to obtain more significant results, showing that different users found a certain set of behaviours more suitable for their purposes than the others. However, it has been difficult to determine a clear pattern among the variables investigated for inclusion in the computational behaviour model to match user characteristics and robot features preferences.

According to this research outcomes, it has been challenging to determine a precise and general definition of the personas-based computational behaviour model. However, several statistically significant variables and trends were found among users' data that still made possible to define an initial model to describe the results of our novel approach and the steps to be followed by the HRI community in future work of this research. The rewards of successfully modelling people's interaction with robot companions are high in the field of HRI. The creation of this model to adapt the HRI system to the users' preferences prior to the interaction presented several difficulties throughout the investigation. This was a continuous learning process that helped understanding the underlying problems for the creation of the model. These results are expected to positively contribute to the HRI field by supplying other researchers with a better insight into the possibilities of integrating the personas technique as part of a computational behaviour model for robot companions. The results from this research could open up new discussions in the HRI field regarding the methodology applied and the future work that could be done to further evaluate and build on the research findings.

In order to summarise the work done during this research, the research questions defined at the beginning of this dissertation are addressed. They guided this research and helped focusing on the direction after the analysing of results of each of the experiments carried out during this investigation. The research questions defined at the beginning of this dissertation were as follows:

- *RQ1*: Which system architecture should we define in order to create a computational system able to automatically adapt a robot companion's behaviour to users based on their needs?
- *RQ2*: Would people with a similar background, characteristics and personality prefer the same robot behaviours and responses during the interaction?
- *RQ3*: Which are the most significant variables found that could help identifying the users' preferences and needs so we are able to adapt the system appropriately?
- *RQ4*: Which are the advantages and disadvantages of integrating the concept of personas into the development process of a computational behaviour model for robot companions in smart homes?
- *RQ5*: Which robot features should be adapted based on the research outcomes investigated during this dissertation?

As part of the research process, a centralised system architecture was defined to enable the integration of the different modules that developed during the investigation. Scalability and modularity are the main characteristics that the system architecture presented in Chapter 4 defines in order to suit the purpose of this research. The success of using this architecture during the whole investigation process, and its capacity of adapting to changes during the iterative cycle, helped answering this first research question (*RQ1*). It could state that the centralised architecture facilitated the integration of the different modules created and the continuous modification of the data required by the system to run the studies. In addition, a common communication data interface was shared between modules, as they all were connected to the same database, which increased the consistency between the system components.

In order to answer the second (*RQ2*) and the third (*RQ3*) research questions, two successive studies were performed to evaluate the user's preferences when interacting with a companion in a home environment. During the *Experiment 2*, participants individually evaluated the two different feature levels, *Low* and *High*, for each of the robot features that were presented during the study. In the *Experiment 3*, participants were asked to select their preferred scenario from the three different ones presented during the experiment. Each scenario represented a persona in the system and displayed a distinct combination of robot features that modified the robot companion's behaviour during the interaction. Based on the results from these two studies, participants with similar characteristics, considering the personality and preferences collected during the pre-experiment questionnaire, did not always choose the same preferred robot features when interacting with a robot companion.

After analysing the outcomes from the two studies, the high variability found in the results was depicted for the variables evaluated when grouped by participants preferring the same robot feature or scenario, depending on the first or second study respectively. This answers the second research question (*RQ2*) and shows the difficulties of modelling people when interacting with robot companions in a smart home. The sample size could have been pointed as one of the factor to explain this outcome, however, the second study, where the sample was bigger, still showed the same sort of trend after the analysis of results. Regarding the third research question *RQ3*, the statistically significant variables found will be presented in Section 7.2. During the investigation of this question, it was not possible to identify as many significant variables as expected, even so interesting trends were found in the results that could open up new research directions in the HRI field. For instance, the positive correlations found between certain pre-questionnaire variables, expressing participants' thoughts prior to the interaction, and their evaluation after performing the study, could be further investigated (see Section 6.7.3).

The fourth research question (*RQ4*) was addressed in the *Experiment 3*, where an evolved version of the personas-based computational behaviour model was presented for evaluation. The knowledge from the previous studies was used to define this new approach, so it was possible to analyse the success or failure of integrating the technique as part of a computational behaviour model. The personas technique was already introduced into the field by other researchers, as pointed out in the literature review, however, it was not defined as the central component of a behavioural model to adapt robot companions to the user's needs. Several advantages in using the personas technique were identified during this research. The technique helped to design the experiment and the combination of robot features that should be defined for each scenario. In this way, the inclusion of participants during early stages of the development process were avoid, thanks to the previous data used to define the initial model, and the results have shown that the robot's social skills were still found satisfactory by the users of the system during the first encounter. Finally, and even though the model created partially fulfilled the initial expectations, the personas technique and its integration as part of the computational behaviour model allows to automatically identify the types of users that the system will interact with during the studies. Regarding disadvantages, it could be pointed out the difficulties finding the match between users and personas as the most challenging issue. It was not as straightforward as initially thought to find the variables to fulfil and fully explain this match. At the same time, defining a certain number of personas in the system could be found laborious, as well as determining the number of them to satisfy the requirement of each particular system. Nevertheless, it was found that three personas could be suitable in a environment similar to the one presented as demonstrated during the iterative process.

Finally, the fifth research question (*RQ5*) can be addressed based on the research outcomes pointed out during this dissertation. The number of robot features initially defined, see Section 4.3, were based on the selected robot companion characteristics, so each researcher should slightly modify those accordingly to the robot used. Therefore, the scenario presented during of the experiments, *Experiment 2* and *Experiment 3*, were created as a combination of the different robot features being modified and the capabilities supplied by the environment where the studies took place. For example, it could be difficult to design an *Robot Kitchen Assistance* scenario in places where such a facilities cannot be found or the access for a robot is difficult, so researchers should adapt this scenario and the robot behaviour associated to different environments. Based on this research outcomes, the *Robot*

Expressiveness and *Robot Proactiveness* seems to play an important role during the interaction between humans and robot in a smart home. Users were able to distinguish the differences, see results of Chapter 6, and they made a preference over the different overall behaviours shown by the robot in each scenario. In general terms, the modification of the *Robot Approach* will depend on the particular situation inside the scenario, based on the experiment performed. People could tends to prefer to keep the distance with a robot companion, but when it comes to situation where something needs to be placed into the robot or the touch screen needs to be used, a closer approach could affect the way in which a users sees the robot. On the other hand, the *Robot Assistance* or *Robot Communication* modifications, initially evaluated in *Experiment 2*, were set as default during the *Experiment 3* as per the results in the *Experiment 2* where the majority of users indicated their preferences for a *High* condition independently of the users characteristics. *Robot Emotions* were not considered during this research, so this could be something to consider in future research. The overall results highlight the importance of personalisation of robot behaviours and their adaptation to the final users who they will interact with.

7.1.1 What Have I Learnt?

During the investigation of our novel approach, several difficulties and unexpected results were identified which enabled the possibility of gaining a deeper knowledge of the design of HRI studies and the development of a computational system to adapt robot behaviours to users' needs. For instance, it was important to learn how to interpret the user's requirements and adapt the robot features to those before the performance of the studies. The definition of personas helped to achieve this, and evidence of this achievement can be found in the third study, *Experiment 3*.

The design of the scenarios and robot behaviours were based on the definition of the personas of the system. After this study, participants found themselves more comfortable in one of the three scenarios presented, and even when the majority of participants preferred the first scenario, the other two scenarios were evenly distributed among the number of participants. This is an indication of the suitability of the scenarios and behaviours created.

An introduction of the UH Robot House's facilities and the robot's capabilities were presented to all participants prior to each experiment, see Table 1.1. Nevertheless, external factors may have affected the way in which users rated their interaction with the robot companion. It has been difficult to determine the causes of certain unexpected results obtained during the study. For instance, inexperienced HRI studies users stated that all the robot features that were evaluated, i.e. both the *High* and *Low* levels of these features, were found satisfactory for them during the interaction. This affected the users' rating during the study, and then the results. In order to address this issue, a different evaluation strategy was developed. A second session was introduced in the latest experiment in order to illuminate reasons for the answers given in the first session and to double check individual user's thoughts about the interaction with the robot companion. It could be hypothesised that participants must have been overwhelmed by the amount of information presented at the same time when first interacting with the system. Re-evaluating the system has been found beneficial for our particular investigation purposes.

An interesting observation was to find that the user's expectations are quite high due to our current immersion in technology. In our opinion, the personalization of robot behaviours when interacting with humans should be addressed during early stages of the development process in any HRI system to enhance the interaction during the first encounter. Non-expert HRI participants seem to quickly adapt themselves to the new situation during the interaction with the companion, which could make users lose their interest in the system in a short period of time. Researchers in the field should work to avoid these sort of undesired situations during an HRI study.

Finally, integrating the personas technique into the development process of HRI studies was more difficult than initially thought. The first problem was to identify preference patterns when interacting with robot companions during the studies. Based on the data analysed, some significant variables and tendencies were found, but these could only partially explain users' preferences during the interaction. The findings still allowed us to define an initial behaviour model to be applied in HRI, nevertheless its limitations should be taken into consideration (see section 7.4).

7.2 The Personas Behaviour Model Approach

The following table (see Table 7.1) depicts the pre-questionnaire variables found as statistically significant across all the studies. These variables are used to define the relation between users' variables and robot features when participants were asked about their preferences during the interaction. The main group of variables to be considered in the model are the *User's Personality*, defined through the TIPI questionnaire, the *User's Comfortableness Interacting with Robots*, defined through the three variables represented in the table and the *User's Preferences* prior to the experiment and expressed during the pre-questionnaire. Refer to Appendix C.4 to find the pre-experiment questionnaire and the scale used for each group of variables. The values are calculated from the group of participants selecting the same preferred scenario in the final study, see Section 6.7. These values will be used to compute the similarity between participants' answers to the pre-experiment questionnaire and the personas' values defined in the table, see Section 4.5. Based on the research findings, only the set of variables found statistically significant and represented in the table should be evaluated. Once again, it is important to remark that due to the difficulties found during this investigation, these values should be just applied to a similar research environment and robot companion used for evaluation. Unfortunately, it is not possible to generalise the behavioural model without first understanding its limitations and adjusting the data to the experimental environment where this is going to be tested.

Group Variable	Variables	Jessica	Simon	Matthew
Personality	Extroversion	4.3	3.0	3.4
	Agreeableness	4.8	4.5	4.3
	Conscientiousness	5.4	5.5	4.9
	Emotional Stability	4.7	5.2	4.2
	Openness	5.8	4.5	4.5
Comfortableness	Being Approached by Robot	4.0	2.5	3.0
	Close to Robot	4.0	3.0	3.0
	Same Room as Robot	4.0	3.5	3.0
Preferences	Expressiveness	3.0	2.0	2.0
	Proactiveness	2.0	2.0	2.0
	Approach Distance	1.5	2.0	2.0
	Interruption Level	2.0	2.0	2.0

Table 7.1: Statistically significant relationships defining our personas-based computational behaviour model.

Once participants are matched to one of the pre-defined persona in the system based on similarity, the following guidelines can be used to define how the robot's behaviours should be modified during the interaction in order to adapt those to the user's needs. Table 7.2 represents the final version of the behaviour model described in this dissertation. Three personas were selected, based on the research outcomes, to guide the definition of the robot behaviours displayed during the interaction between a user and robot in a domestic environment. The robot features were defined as general as possible to suit the majority of robot companions found nowadays, however, this model should be re-evaluated and adjusted as needed when applied during the design and development stages of a different HRI study in a similar environment.

Robot Feature	**Conditions**	**Jessica**	**Simon**	**Matthew**
Communication	Advance Interface	X	X	X
	Simple Interface			
	Robot's Voice	X	X	X
Proxemics	Personal Zone	X		
	Social Zone		X	X
Assistance Level	High	X	X	X
	Low			
Expressiveness	High	X	X	
	Low			X
Proactiveness	High	X		X
	Low		X	

Table 7.2: The personas-based behaviour model defined after our investigation

7.3 Contribution to Knowledge

This dissertation sets out a novel approach to investigate the personas technique in the field of HRI. The personas technique was defined as the core component of the computational behaviour model investigated. This model helps modify the robot companion behaviour to suits the user's characteristics when first interacting. The main motivation was to bridge the gap between the design of HRI studies and implementation of social skills in robot companions in order to make them be accepted by humans. There are well known difficulties recruiting participants for HRI studies and asking them to perform different tasks repeatedly. This data collection puts a real burden on participants of the system and it should be assisted by the creation of techniques able to adapt the system to the user's preferences and needs at first encounters. The incorporation of this technique into the HRI field allows the reduction of the amount of trials carried out during early stages of the research, and at the same time, provides a tool to keep the robot's social skills level expected by users. During the investigation of this novel approach, several modules have been created and integrated into the system architecture in order to develop a suitable environment to study the personas technique during this research.

The ARS presented in Chapter 3 was created and evaluated as an extension of the current context-aware system installed in the UH Robot House. Robot companions must present social skills during interaction in order to increase their acceptability by users. The system created improved the robot's social capabilities by allowing the system to recognise the daily living activities performed by the users and adapting the interactions to the current situation. The robot companions used at the UH Robot House later utilised the ARS in other research projects run by the department. The main contribution was to develop a system for non-expert users based on general knowledge of the environment and which can be adapted to other environments besides the one where it was initially developed. The definition of the rules can be expressed through natural language and based on the user's knowledge of the system. As presented in Appendix A, the system was tested and validated with an adequate confidence level. The accuracy value achieved, over 80%, exceeded the initial expectations and demonstrated the capabilities and performance of the system. It is important to clarify that the ARS was intended to trigger and present an identification at the starting point of any activities, and not at the ending points of these. Two reasons led to take this approach; firstly, it was difficult to reliably detect when certain activities have finished due to sensing hardware limitations, and secondly, the beginning of each activity was considered as the optimum moment at which a robot companion should interact with the user to offer its assistance. Nevertheless, users should be able to help the robot to disambiguate the current status of the system when the end of a certain activity cannot be recognised but this action is needed to carry on the normal flow of the interaction. Any additional information will help to improve the robot's awareness of the current situation when interacting with a human and thus further enhance its abilities to make decisions and interpret correctly.

Once the system was configured, the investigation and evaluation of the personas computational behaviour model was carried out by means of two different experiments, *Experiment 2* and *Experiment 3*. To the best of my knowledge, only a few HRI studies introduced the personas technique in the field (see Chapter 2), but none of them introduced it as part of a computational behaviour model to adapt robot behaviours to users in domestic environments. The personas technique supplied a set of archetypes, defining their characteristics and their goals in using the system to be developed; in this particular case, a robot companion interacting in a smart home. The main target was to define this model to provide an initial set of robot behaviours to adapt the companion based on the matching between the user and the pre-defined personas of the system. This research investigated and evaluated the novel approach and explore its suitability for designing and developing HRI studies. As part of the iterative methodology adopted, the initial behaviour model was continually expanded and modified based on the results obtained during each of the experiments performed during the investigation. After the analysis of date, a set of significant variables were identified which partially explained the reasons why different types of users prefer certain robot behaviours over others. These variables will be used to match users and personas as part of the computational model, so the robot's behaviour will be adapted to the user when first interacting. The definition of the model allows us to collect user data just during the evaluation stage instead of the development stages of the system. This definitely helps to reduce the burden put on participants for the definition of HRI systems, as defined in the introduction of this dissertation, see Chapter 1. In addition, robot behaviours can be pre-adjusted to user needs without performing long-term experiments beforehand in order to train the system for each individual user's preferences.

After the definition of the model based on the investigations done, see section 7.2, three were found a sufficient number of personas to be included into the model in order to guide the definition of robot behaviours in our particular system. The use of the model within a comparable environment and robot companion could provide similar results, however, each new study should adapt the system to its different requirements and characteristics prior to utilise it. The model was always meant to be as general as possible in order to be applied to any robot companion in a similar context, however, due to the difficulties found during the investigation, declaring the creation of a model capable of working *out of the box* in any desired environment cannot be claimed. Nevertheless, it has been important to with the HRI community the steps followed and the research process executed to investigate a novel approach considering the personas technique as a core component of a computational model to adapt robot behaviours to user preferences. This should help other HRI researchers to use this experience and apply the outcomes to their particular problems or investigations inside the field. On the other hand, the use of personas to define the system and create different robot behaviours has been shown as a useful methodology to develop HRI system. The initial robot behaviours defined in the first model created, see Chapter 4, and its successive versions, see Chapter 6 and section 7.2, were positively accepted by the sample users. During the latest experiment, *Experiment 3*, participants' preferences were distributed across the different scenarios presented. The expansion of the number of personas and the robot behaviours defined in the model will depend on the capabilities of each system, and the possibilities of each system to create different robot behaviours that can still be distinguished by users during the evaluation process.

It could be concluded that this research investigated the integration of a novel approach into the development process of HRI studies were the personas technique was the core component of the system. The user's characteristics and needs are taken into account from early stages of this development process, but this approach will contribute to avoid the collection of extensive user data to train and adapt the system for each individual participant. The definition of the model is used to adapt the robot behaviour to user preferences prior the interaction. This research shows to the HRI community the advantages and disadvantages of the novel approach investigated, as well as the difficulties faced and the directions followed to surpass those. The outcomes and discussion presented should inspire other research in the HRI field to look at different approaches knowing in advance the problems that they could find during the process. Future research on the topic should take advantage of our evaluation process and findings.

7.4 Limitations

During this research, several limitations were identified in the development of the system presented. The issues found during the investigation were addressed as part of the iterative methodology followed, however, it was difficult to address all the possible factors affecting the research results. This section describes the limitations found and determines how they could be covered in future work of this research to solve the problem identified.

As mentioned previously, some of the research outcomes could be affected by the sample size or the type of users recruited. All participants were a mixture in terms of background, technical experience and age range, so perhaps a more focused sample would give a clearer picture of the outcomes obtained in this research, although this cannot be guaranteed. However, the main desire was to test the system against different types of users to achieve a general computational behaviour model to be used without restrictions in this regard. Nevertheless, the outcomes achieved and described during this dissertation are useful to guide future work on this research and show other researchers the direction to take. However, the limitations regarding the non-parametric test used and the generalisation of the results to other areas of the population must be taken into account. For instance, elderly people, who were not representative in our sample and difficult to recruit during the research process. Responses from this age-group to the interaction with the robot companion could be expected to differ from our mix age-group sample's responses. The recruitment of a varied and balanced sample for HRI studies is quite a difficult task to be achieved, so researchers in the HRI field need to learn to interpret the outcomes based on this known limitation.

Another limitations to consider include the system hardware and robot capabilities or appearance. For instance, the capabilities shown by the robot companion used in the UH Robot House are constrained by the space where the robot moves and the own robot specifications. The robot appearance could play an important role during the interaction and it is difficult to measure how this may affect the results. The initial set of robot behaviours defined considers common robot features for both the Sunflower and the Care-O-Bot robot companions. These selected features, e.g. LED lights, head movements, torso movements, voice, tablet PC, and the scenarios used to shown them to users could be replicated by other companions nowadays, however this assumption could be listed as another limitation of the system.

For instance, a more advanced robot companion would extend the possibilities of investigation and the outcomes could differ from the ones depicted. As presented during this dissertation, two different behaviours were defined for each robot feature presented, but these behaviours were selected due to the hardware limitations of the companion and the impossibility of creating a middle behaviour capable of being distinguished by users of our system. As a note aside, the *Scenario 1*, represented by the persona *Jessica*, was the most popular among users when asked about their preferred one during the final study. Each of the robot features displayed during this scenario was the highest that the Sunflower robot companion could adopt when interacting with the user. Therefore, it seems that users tend to select the best set of robot features that the company could possibly show during the interaction. The use of a most sophisticated robot companion including a wider range of features will allow the expansion of the model in terms of the number of personas and the robot features to be modified during the interaction. This would create room for further investigations with different types of robot companions.

Finally, the model was created to define just the initial behaviour that the robot companion should adopt during the first encounter with humans. The creation of just two or three personas to cover all possible scenarios can be pointed as another limitation, but the investigation was focused on presenting this methodology and way of thinking to the research community rather than covering all the cases. A more extensive investigation was outside the scope of this research due to time restrictions. The sample selected, the identification of user characteristics, the time of the day when users interacted with the companion or the sort of interaction and lack of a dynamic interaction depending on the kind of study performed, eg. the *Experiment 2* or the *Experiment 3*, can be definitely consider as limitation of this research, but at the same time they are difficult issues to face inside the HRI field.

To summarise, a combination of a more focused and bigger sample, combined with a wider range of robot features to be displayed during the interactions and used to assist participants on a large number of tasks performed at home, would definitely expand the possibilities for investigation of the system presented in this dissertation. However, the difficulties modelling the user behaviour when interacting with a companion was shown. It seems complicated to define a pattern that can be adapted to any single user that our system could interact with.

7.5 Future Work

During this research, several points could be modified in order to expand the system's capability in the long term. The feedback of participants and the experience acquired across the three experiments performed, see Table 1.1, supplied a good insight into issues that should be addressed to improve the system. Currently, humans live in a world surrounded by technology and it is difficult not to compare existing devices to new ones and get used to the increase in performance on the latest model available. This issue could affect HRI studies as participants' initial expectations may be quite high when first interacting with the system. Smart homes and robot companions are still lacking the introduction of technological advances that make them as reliable and accepted as other devices or technologies in the market. There are too many limitations that should be addressed before companions can be introduced into our houses in the same way that others devices currently are. Regardless of these limitations, researchers in the field have still to take advantage of the resources available and investigate techniques that could be applied in future studies when current hardware limitations will be addressed.

The creation of a computational behaviour model for robot companions has proven to be a difficult task to address. The results and the final version of the model presented for the purpose of this dissertation should not be generalised without first analysing the similarities between the new system and the one where this investigation took place. This is the reason to believe that further research on the topic in a different environment could bring interesting results to support, or even contradict, our findings. Looking at the UH Robot House and how the system developed was kept compatible with the rest of the house's components, it could be worthwhile to investigate our approach using the Care-O-Bot robot companion, or a similar companion that may be integrated into the house in the future, to compare the outcomes.

Another point to consider could be the expansion of the model in terms of personas and robot capabilities. This would be only possible when the features of the robot companion allow to define a greater combination of behaviours to be presented to users. This must still be distinguishable by participants during the interaction. As mentioned in previous chapters, the limitation of creating similar behaviours must be considered before designing the system as users will not be able to differentiate them. Also, it could be worthwhile to re-evaluate the final version of the model using a bigger or more focused sample. It could be really interesting to compare the latest results with the results obtained from a bigger sample. These new lines of investigation could bring new ideas, explanations or confirmations to the outcomes presented in this dissertation.

To conclude, a different approach build upon this research could be addressed. The expansion of the system in order to adapt robot behaviours to users' preferences during long-term studies, seems an interesting research direction. Starting from the initial model definition, a different module should be integrated to modify the model based on users' feedback and preferences during the study. The system should learn from previous experiences and be able to predict the best set of behaviours to be applied. In the HRI field, long-term experiments will alter the way in which users initially interact with companions, so a different approach should be considered to fulfil user's expectations beyond the first encounter.

Chapter 8

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Appendix A

Publications

Knowledge-driven User Activity Recognition for a Smart House. Development and Validation of a Generic and Low-Cost, Resource-Efficient System

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***Abstract*—Our core interest is the development of autonomous and socially interactive robots that may support elderly users at home as part of a smart home, i.e. a home equipped with a sensor network that may detect activities of daily living such as preparing food in the kitchen, having meal in the living room, watching the television, etc. The current paper focuses on showing the design and implementation of a low-cost, resource-efficient activity recognition system that can detect user activities without the necessity of collecting a large dataset to train the system. Based on common-sense knowledge from activities of daily living, we generated a set of rules for defining user's activities in a home setting. These rules can be edited and adapted easily in order to accommodate different environments and daily life routines. The approach has been validated empirically with a pilot study in the University of Hertfordshire Robot House. The paper presents results from a study with 14 participants performing different daily life activities in the house. The results are promising, and future work will include the integration of this system in a Smart House used for Human-Robot Interaction studies. This may help develop context-aware robot companions capable of making better decisions to support users in their daily activities.**

***Keywords*-Activity Recognition; Smart Houses; Context-Aware**

I. Introduction

In the field of Human-Robot Interaction (HRI), many researchers are interested in understanding how humans interact with robots in different environments [1]. The incorporation of social skills into robots' responses to achieve smoother interaction with humans remains a significant challenge. Many studies (e.g. [2] [3] [4]) from the Adaptive Systems Research Group at University of Hertfordshire have been carried out with the aim of gathering findings that help us understand how people interact with robots in a domestic environment, and hence to develop robots which exhibit a greater awareness of context when interacting with humans. The Robot House (see Figure 1) is the naturalistic environment used by our research group to perform this variety of experiments.

Fong et al. [5] assume that humans tend to interact with robots in ways that are similar to how they interact with other humans, i.e. humans expect certain social characteristics from robots. For instance, in the area of assistive robotics, the robots will become part of people's lives, so these social skills have to be brought out during interaction. Context-aware robot companions would have the ability to detect what kind of activities users are performing at home. Human activity recognition systems will supply the necessary information to allow these robots adapt their behaviour to the ongoing activity, and increase their social skills aforementioned.

One of the current problems pointed out in the literature, is the large variety of datasets necessary to create accurate activity recognition systems [6], and the difficulties in recruiting participants for the experiments [7]. We therefore developed a different method to avoid involving users in extensive studies of data collection during the whole process of system development. This point is particularly important when working with elderly people or people with special needs, which are the target user groups that our research is concerned with. Asking e.g. elderly people to spend several days or weeks engaged in certain activities to generate training data for the system puts a huge burden on them. The Activity Recognition System (ARS) that will be presented in this paper takes into account this issue. The knowledge-driven approach [8] used allowed us to develop the low-cost, resource-efficient system, in which participants were involved just during the validation stage.

Our research follows two well-defined directions. Firstly, the incorporation of social skills in robot companions to create more natural human-robot interactions in living environments. Smart homes' facilities will help to develop these skills (e.g. the non-intrusive sensor network installed in the Robot House). As Chan et al. [9] mentioned, sensor-embedded houses provide context information without disturbing users' daily activities, creating greater comfort and well-being. Secondly, we avoid the involvement of users during the training phase of the development of the system by the use of knowledge-driven approach. Following these two directions, we have created a functional activity recognition system that was tested with 14 participants in its validation stage.

The remainder of this paper is organised as follows: Section 2 discusses related work. Section 3 presents the research question and goals. Section 4 describes how the activity recognition system has been created, and the structure of the set of rules defined on our system. Section 5 describes design and procedure of the experiments carried out. In Section 6, the analysis and the evaluation of these experiments are depicted. Section 7 reviews how the research questions have been accomplished. Finally, we conclude this paper in Section 8.

II. Related Work

The HRI field as a distinct branch of academic activity first emerged in the mid 1990s, although the robot's behaviour and their consequences for humans have been studied in several fields. Goodrich et al. [10] present a survey of current and historical research into HRI. The field is focused on studying robotic systems that interact directly or indirectly with humans. The understanding, evaluation and appropriate design of these systems should facilitate satisfying and naturalistic social interaction between robots and humans. For an assistive robot to be useful for its user in a home context, the ability to recognize and respond to human activities is essential.

As we mentioned in Section I, the integration of tools such as human activity recognition systems is a first step towards the target of naturalistic interaction between users and robots. In the field of Smart Houses, we can find a huge variety of activity recognition studies, but relatively few are oriented towards robot companions and take into account the need for a reduction of time invested by users in the development of such systems, or the realistic experiments conditions pointed out by Logan et al. [11]. Our ARS has been designed and evaluated based on these principles.

In the literature, two main categories can be found regarding activity recognition systems [8]. The first is based on visual sensors, e.g. camera- based systems to monitor behaviours and

Figure 1. The UH Robot House layout and sensor arrangement. 59 sensors are available in the house, but only 52 were used and shown here. The two cameras' locations during the experiments are represented in this picture.

changes in the environment [12] [13]. This approach combines computer vision techniques and pattern recognition. The second category is based on sensor networks for monitoring activities in Smart Houses. It can be subdivided into data-centric, logical or semantic approaches. These approaches typically require extensive data collection with potential users of such systems. The data is then analysed using data mining or machine learning techniques to build activity models, which can then form the basis for activity recognition systems. The knowledge-driven, rule-based system approach that we describe in this article belongs to this second category. Similar approaches can be found in the literature [14] [8], but in their evaluation stages participants were told to perform certain activities following a sequence of actions. The approach here presented is capable of recognizing user activities without restricting the way in which users perform those. The use of a non-intrusive sensors helped us create a natural environment. In our view, wearable sensors could affect users' comfort and seem particularly problematic for elderly people.

Other issues have been taken into consideration as well. The system was designed to be easy to move and install in other similar environments without the necessity of specialized knowledge on how these systems work and need to be set up. The rules and sensors are defined in the configuration files (see Section IV-B), followed by a natural language description in order to make the system more understandable. A key advantage of this approach, is that the rules are explicitly represented rather than implicitly represented (e.g. within a Bayesian network [15] [16] or a Hidden Markov Model implementation [17] [6]). This allows us to inspect and manually change or update the rules if needed. As part of the ACCOMPANY project [18], our research in the Robot House will be incrementally developing more complex HRI scenarios for home assistance, so it is important for us to be able to have a system that can be extended and modified easily by non experts, and at the time, keeping the development cost of the system down. We argue that developing a low-cost and resource-efficient system (e.g. the ARS presented), is an important prerequisite for a possible future use in real world applications.

III. Research Questions and Goals

The purpose of this article is to present the development and implementation of the knowledge-driven ARS system and its first validation study. The comparison between the activities recognized by the system, and the actual, observed activities performed by the user during several sessions, will determine the accuracy level of the system and its capacity to be integrated into future HRI studies. The data collected in the first validation study will be used to improve the first set of system parameters and to suggest new features for future versions of the system. In addition we try to learn about users' behaviour in a natural home situation, and understand how robot companions could behave in such home environments. Our research questions are:

- Q1. Is our ARS generic enough to detect different users' activities without the system being individually trained for the users?
- Q2. Can the ARS achieve an accuracy higher than 80% in the controlled experiments?
- Q3. Can the ARS achieve an accuracy higher than 80% in the uncontrolled experiment?
- Q4. What are the advantages and disadvantages of the ARS presented in this paper?

The percentages defined in questions 2 and 3, have been set at these values in order to validate the system with an adequate confidence level. This will ensure a reasonable reliability of the environmental information that will be sent to robot companions in future HRI experiments. An accuracy over 80% seems sufficient since robots' behaviour will not solely be based on the information received from the ARS, but supported by the Robot House's system that makes decisions based on further environmental information. Therefore, we expect that this additional information supplied by the ARS help us improve the robot's awareness of the situation and thus further enhance its abilities when interacting with users in a living environment.

IV. Human Activity Recognition Framework

A. Robot House Sensor Network Description

Two different but complementary commercially available sensor systems, the GEO System and ZigBee Sensor Network, were installed in the Robot House. Both the GEO System and ZigBee Sensor Network have a refresh rate of 1 Hz, which is deemed as adequate to detect user activities.

The GEO System [19] is a real-time energy monitoring system for electrical devices. It is used to detect the activation and deactivation of electrical appliances by the Robot House's users (e.g such as opening the refrigerator or boiling water in a kettle). The status of the electrical appliances connected to this system can be queried from the GEO System database.

The ZigBee Sensor Network [20] is used to detect user activity that cannot be detected by the GEO System such as opening of drawers and doors, occupation of chairs and sofa seat places, opening of cold and hot water taps etc. The ZigBee Sensor Network consists of five ZigBee Wireless modules, which are spread across the Robot House. Together they transmit readings from a total of 26 reed contact sensors, 4 temperature sensors and 10 pressure mats to a ZigBee gateway (XBee Gateway X4). The ZigBee gateway forms an interface between ZigBee Sensor Network and the Robot House Ethernet infrastructure, where the ARS resides.

B. Implementation

The ARS was developed in Java with a local MySQL database for logging purposes. The software consists of the following four different modules:

Table I
BEHAVIOUR CODING SCHEME. ACTIVITIES CONSIDERED FOR THE ACTIVITY RECOGNIZER.

Code	Behaviour	Description
ut	Using Toaster	The time that this appliance is switched on
uk	Using Kettle	The time that this appliance is switched on
pf	Preparing Food	The user is in the kitchen preparing some food
pcd	Preparing Cold Drink	The user is having some cold beverage
phd	Preparing Hot Drink	The user is preparing either tea or coffee
co	Computer ON	The time that this appliance is switched on
uc	Using Computer	The user is sitting in the dining area and using the computer
sd	Sitting Dining Area	The user is sitting in the dining area
lt	Laying Table	The user prepares the table before having meal
md	Having Meal Dining Area	The user is sitting in the dining area and having mea
std	Spare Time Dining Area	The user is reading a book or newspaper in the dining area
wt	Watching TV	The user is sitting in the living room and watching the television
t	TV ON	The time that this appliance is switched on
slr	Sitting Living Room	The user is sitting in the living room
stl	Spare Time Living Room	The user is reading a book or newspaper in the living room
ml	Having Meal Living Room	The robot reminds the user about some medicine
ct	Cleaning Table	The user finish the meal and tidy up all the objects used

- ZigBee module. Manages sensor data from ZigBee Sensory Network.
- GeoSystem module. Pulls sensor data from GEO System Database.
- Activity Recognizer module. Analyses the sensory data retrieved from the ZigBee Module and GEO System Module to determine the user's activity.
- User Interface module. Displays and records the detected user's activities and sensory information to a local database (MySQL) and external log files.

The ARS has been tested on both Linux and Windows systems, with a local MySQL database for data logging purposes. The system is configured by using two XML files. The first configuration file contains the representation of the Robot House sensor network (i.e. mapping sensors' IDs to their symbolic names), and the second configuration file defines the semantic rules used by the ARS to detect user's activities in the Robot House (see Section IV-C). These rules were set based on an initial set of trials and the common-sense knowledge which activities of daily living (ADL's) are based on [8]. In future work, the parameters could be refined based on the information gathered after this study. We have to consider that this first experiment is part of the learning process that we have to follow to achieve our final research goals.

Two issues have to be pointed out in regards to the system. Firstly, the ARS is intended to trigger and present an identification at the starting point of the activities studied (see Table I). We consider that the beginning of each activity is the optimum moment at which robot companions should interact with users to offer their help. Secondly, the possibility of migrating the system to other similar environments has been considered during the development process, so that the editing, redefinition or adaptation of these two configuration files would be sufficient to run the system in a new environment.

C. Rule Definition Example

In this section, we show briefly how the ADL's rules have been defined following common-sense knowledge which make the system understandable to any researcher using it. We studied a variety of activities that will be useful in assistive robotics scenarios in future stages (see Table I). These activities can be described as the combination of sensors activated in the environment, and previously performed activities, namely context-activities. Thus, the system manages two different kinds of activities. Low-level activities are those that are detectable by a single fixed sensor (e.g. the user sitting on the sofa). High-level activities are those that can only be detected by utilising a combination of different sensors, or a combination of different sensors and low-level activities detected. Based on that, each rule is defined using the following tags:

- Duration: The maximum time the activity remains activated in the system. Some activities, e.g. *Using Computer Dining Area* and *Sitting Living Room* (described below), do not consider this tag as they are deactivated based on their associated context-activities or associated sensors' status values.
- Location: The location where the activity is performed.
- Context: Set of activities that has to be fulfilled before the activity is activated. Some activities, e.g. *Sitting Living Room*, do not have any context-activity associated with them. *Interval*: Time window in which the context-activity is relevant for the detection of the activity. *Status*: The required context-activity's state for the activation of the activity.
- Threshold (Sensors' attribute): Minimum value necessary to consider the activity as activated. It is based on the accumulated weight of the sensors triggered.
- Sensors: Each of the sensors involved directly in this activity. They have a *Status*, *NotLatching* (True: The sensor's weight will be only added to the accumulated weight while it remains on, otherwise, its weight is subtracted from the accumulated weight; False: the sensor's weight is added to the accumulated weight once it is on regardless of its later state), and *Weight* fields. Some activities, e.g. *Using Computer Dining Area*, do not have any sensors associated with them.

We can see below the examples rule *Using Computer Dining Area* and *Sitting Living Room*. More examples are available from the author on request:

```
<Activity Name="Using_Computer_Dining_Area">
    <Duration>Nil</Duration>
    <Location>Dining_Area</Location>
    <Contexts>
        <Context Interval="0" Status="activated">
         Sitting_Dining_Area</Context>
        <Context Interval="0" Status="activated">
         Computer_ON</Context>
    </Contexts>
    <Sensors Threshold="0.0"></Sensors>
</Activity>

<Activity Name="Sitting_Living_Room">
    <Duration>Nil</Duration>
    <Location>Living_Room</Location>
    <Contexts></Contexts>
    <Sensors Threshold="0.50">
     <Sensor Status="on" NotLatching="true" Weight="50">
         Sofa seatplace 0</Sensor>
     <Sensor Status="on" NotLatching="true" Weight="50">
         Sofa seatplace 1</Sensor>
    /Sensors>
</Activity>
```

In the first example, *Using Computer Dining Area*, the activity depends on *Sitting Dining Area* and *Computer On*, but no sensors are associated with the activity recognition. For this reason, *Duration* and *Threshold* tags are not considered for this activity, as the activity will be activated only when both context-activities are activated. In the second example, the activity is associated with certain sensors, whose *NotLatching* field make their activation compulsory to keep the activity activated as well. Therefore, *Duration* is not considered for this activity, since the deactivation of the associated sensors will deactivate the activity.

Table II
THE OBSERVER XT FORMATTED OUTPUT (LEFT SIDE) AND THE ACTIVITY RECOGNIZER'S EVENT LOGS (RIGHT SIDE). THIS DATA REPRESENTATION HELPED US ANALYSE THE RESULTS AND FIND BEHAVIOUR PATTERNS THAT WILL BE CONSIDERED IN FUTURE WORKS.

Observation	Time_Relative_hms	Duration_sf	Behavior	Event_Type		System	System Events	Time	Time Relative	Delay (seconds)
								08:21:35		
User-001-S2	00:00:00	60.74	Preparing_Cold_Drink	State start		Yes	Preparing_Cold_Drink	08:22:18	00:00:43	00:00:43
User-001-S2	00:00:05	299.88	Preparing_Food	State start		Yes	Preparing_Food	08:21:39	00:00:04	00:00:01
User-001-S2	00:00:21	75.04	Using_Toaster	State start		Yes	Using_Toaster	08:21:58	00:00:23	00:00:02
User-001-S2	00:01:00	0	Preparing_Cold_Drink	State stop						
User-001-S2	00:01:28	16.96	Laying_Table	State start		Yes	Laying_Table	08:23:01	00:01:26	00:00:02
User-001-S2	00:01:36	0	Using_Toaster	State stop						
User-001-S2	00:01:45	0	Laying_Table	State stop						
User-001-S2	00:02:01	50.06	Using_Toaster	State start		Yes	Using_Toaster	08:23:36	00:02:01	00:00:00
User-001-S2	00:02:11	41.32	Sitting_Dining_Area	State start		Yes	Sitting_Dining_Area	08:23:45	00:02:10	00:00:01
						Extra	Having_Meal_Dining_Area	08:23:45	00:02:10	00:02:10

V. EXPERIMENTAL DESIGN AND PROCEDURE

A validation study was conducted by the Adaptive Systems Research Group at University of Hertfordshire in May 2012 to measure the accuracy of the framework previously explained. The Robot House provides a naturalistic and ecologically acceptable environment to carry out studies into ADL's. The main aim was to measure the accuracy of the system in both controlled and uncontrolled scenarios and collect data for future studies. A sample of 14 adults, unaffiliated with the ongoing research, and aged between 23 and 54 was recruited from students and staff of the University of Hertfordshire. All the subjects first completed a consent form, in which they were informed about the voluntary nature of the experiments, before they performed a two-day experiment, one session per day. Each session lasted approximately 20 minutes.

A. Experimental Setup

The experiments took place in the Robot House in which ARS were installed and configured. All the experiments were recorded on video and audio using two different cameras (see Figure 1) rather than relying on self-reporting. One camera covered the dining area and living room, and the other covered the kitchen. They were the only rooms that the participants used to perform the experiments. The cupboards were labelled to make the participants aware of every object's location and create a more natural environment in the sense of knowing where things are located, as they would feel in their own houses. However, they got used to the Robot House facilities after the first session as will be explained in the next section.

The ARS generated two different log files for each participant, one per session. The first file stored information on all the sensors activated and deactivated during the experiment, as well as the decision-making process that the activity recognition algorithm was doing in real time. The second file represents the raw sensory data received from the system during the experiment. These raw data can be used to simulate users living in the Robot House in future experimental scenarios in which robots will be included.

B. Experimental Procedure

The experiments were led by the researcher, who introduced and explained the procedure and the house's facilities to each subject. This section took approximately 10 minutes and was only provided for the first session. After this introductory part, during the first (controlled) session the participants were led by the researcher for 20 minutes, while they were asked to perform a number of specific common ADL's using the Robot House's facilities in the way in which they felt most comfortable with. Thus, they were told what activity to perform, but not how to perform it. In the second (uncontrolled) session, we told the participants to spent around 20 minutes simulating 'living' in the house. They were asked to perform whichever activity (based on the facilities shown during the introductory session) they wished during this period of time. Consequently, we exposed the system to two different situations, controlled and uncontrolled, which would help us measure the system's accuracy and analyse human behaviour at a home environment and discover details omitted in the system, respectively. After each session, the participants were asked to complete a questionnaire. They rated the scenarios and the activities in which they were involved. Basic demographic information of each participant was collected in this questionnaire as well. Note, the order of the conditions was not counterbalanced, since the goal of the study was not to compare the two conditions. Also, it seemed important to first expose participants to the controlled condition which helped them to prepare themselves for the uncontrolled condition.

VI. ANALYSIS AND EVALUATION

A. Behaviour coding

Relatively little work (e.g Logan et al [11]) has combined behaviour coding with user activities in Smart Houses. However, many examples of different data annotation studies can be found in the field of HRI, e.g. [21], and Psychology, e.g. [22]. The coding of the video data of the participants activities helped us analyse each session and identify the important events which we were interested in. The Observer XT software supplied by Noldus Information Technology [23] is a commercial software package used for coding, analysis and presentation of observational data.

The first author of this article was the first coder of all the video material. Additionally, following conventions of behaviour coding, a second coder carried out the same process with 10% of the analysed videos in order to perform the reliability test. The Observer XT and the coding scheme shown in I were used by both coders, both coders were asked to familiarize themselves with this coding scheme before the annotation process. They were told to code activities in which users interacted with some of the sensors installed in the Robot House, in order to generate the sequence of activities that each user had been performed. The outcomes were exported to an Excel files in order to be compared to the events generated by our ARS during the analysis stage.

1) Inter-rater Reliability Test: The Kappa Statistic [24] was used to determine the level of agreement between the two different annotations carried out by the two coders. The annotations were paired in Observer XT, and the kappa value was generated automatically for both sessions. The time windows for the reliability analysis was defined as one second. The kappa value for the combined analysis was 0.75, with overall agreement of 76%. This result represents a good agreement rate for both annotations [25].

B. Data Analysis

A final Excel file was built based on the event lists created using Observer XT and the events generated by our ARS (see Table II). The left side of the table represents the events exported from the software. On the other side, the activities recorded by the system were written down together with their starting time. In this way, the results were shown clearly, and allowed to distinguish 'recognized', 'missed', or 'extra-recognized' activities more easily. The last category represents those activities that fulfilled all the sensor's activations required but they were not performed by the user as evident in the video data. In future experiments, the interaction between the robot companion and the user will help us clarify the real status of these kinds of activities. Moreover, additional tools to support our ARS will be integrated into the Robot House's system during the ACCOMPANY project [18].

A total of 14 participants and two sessions per participants have been considered for the data analysis. We will explain each session separately. The system performance was calculated in terms of precision, recall and accuracy [26] (see Figure 2).

$$Precision = \frac{tp}{tp + fp} \qquad Recall = \frac{tp}{tp + fn}$$
$$Accuracy = \frac{tp}{tp + fp + fn}$$

Figure 2. Precision, recall and accuracy formulas. (tp = true positives or 'recognized', fn = false negatives or 'wrongly recognized' and fp = false positives or 'extra-recognized').

1) Session 1 (controlled): We have to remember that in this scenario the user was lead by the researcher, as we described in Section V. A total of 240 events were coded in all the experiments carried out in this session. The average number of performed activities per user was 17. We got 239 correctly recognized activities, 1 missed activity, and 37 extra-recognized activities were triggered. We obtained a precision of 86,59%, a recall of 99,58% and an accuracy of 86,28%. We found some delay in the recognition of the most complex activities, i.e. those activities involving a major number of different sensors (e.g. preparing food or preparing a beverage). The rest of the activities were recognized with an average delay of two seconds, which is reasonably fast, taking into account the operating system frequency 1Hz).

2) Session 2 (uncontrolled): In the second session, good overall results were achieved too, even taking into account the openness of the scenario which we exposed our system to. A total of 216 events were coded in the experiments carried out during this session. The average number of performed activities per user was 15. We got 200 correctly recognized activities, 16 missed activities and 23 extra-activities were triggered. We obtained a precision of 89,69%, a recall of 92,59% and an accuracy of 83,68%. As stated before, some delay were found on the most complex activities. In Figure 3, we represent these averages delays per activity (e.g. Preparing Hot Drink was recognized with a delay of 35 seconds). The rest of activities were recognized with a similar average delay than in Session 1. The data collected in this experiment will help us understand human behaviour at home and improve the system for future studies.

VII. DISCUSSION

The results presented above allow us to answer the research questions presented in Section III. The approach followed has demonstrated the possibility of creating a low-cost, resource-efficient ARS and presenting it to real users without the necessity of previous training. This is directly related to the reduction of time spent by participants in HRI studies as it was mentioned in Section I. The accuracy in both controlled and uncontrolled sessions exceeded the 80% threshold previously defined in our research questions, which was considered as adequate for the kind of study. Some of the advantages presented by this approach are the creation of a non-restricted and naturalistic system that allows users to behave as they would in their own houses. As we mentioned, in other approaches experiments were typically much more constrained. The use of hidden, non-intrusive sensors installed around the Robot House helped us create this natural environment, as we focussed on avoiding wearable sensors that could make users uncomfortable. In addition, the system can be easily migrated and setting in a similar environment without the necessity of specialized knowledge. The rules and sensors were defined using a natural language in order to make the system more understandable.

On the other hand, the system does have some disadvantages. Firstly, the types of sensors currently used do not allow to determine accurately where the user is located in the house. Therefore, the recognition of activities for two or more users simultaneously cannot be detected directly, as the system is not able to match activities with users. An extra tool, e.g. camera recognition, may be considered in future work. However, this will increase cost and complexity of the system and involve privacy issues. Secondly, the semantic rules used by the ARS were defined based on common-sense knowledge of how a person would carry out the ADL's. A module to modified these initial definitions as the user interact with the system will be considered in future stages of our research.

Once the ARS has been integrated into the Robot House system, we will be able to create much richer scenarios in which robot companions will be aware of users' activities. This will allow us to adapt robots' behaviour to their needs in each situation, and increase robot companions' autonomy to make decisions. A variety of challenging studies will be targeted in future stages of our research.

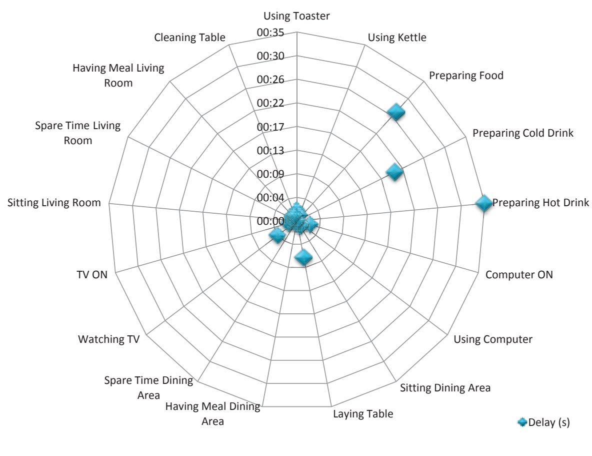

Figure 3. Overall delay per activity in the uncontrolled scenario.

VIII. Conclusion and Future Work

We have presented the development and validation of a knowledge-driven rule system to identify user activities in home scenarios. We tried to build a low-cost, resource-efficient and easily understandable and re-configurable system that is accurate enough to detect a set of ADL's. This approach was evaluated empirically by means of the studies carried out in the Robot House. The experimental environment allowed participants to behave in a similar way that they would in their own homes, as it was reported in the questionnaires. Although the participants did not belong to our target user group, i.e. elderly people, we claim that, due to the general design of our system, the results can be generalized, and if necessary, can be easily adapted to this users group. In future work, the adaptation to individual users and their specific life styles and routines may also be considered. The results achieved fulfil our expectations and answer fully the research questions defined in Section III. These findings motivate us to progress towards our final research target of designing context-aware companion robots for home environments. It can be concluded that the developed ARS could be integrated into future experiments of our research.

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A Different Approach of using Personas in Human-Robot Interaction: Integrating Personas as Computational Models to Modify Robot Companions' Behaviour

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***Abstract*— The current paper focuses on a novel integration of the Personas technique into HRI studies, and the definition of a Persona-Based Computational Behaviour Model for achieving socially intelligent robot companions in living environments. Our core interest is the creation of companions adapted to users' needs to support their activities of daily living. The aim is to create a mechanism that allows us to develop initial robot behaviour, i.e. behaviour when first encountering the user, which is already adapted to each user without the necessity of collecting in advance a large dataset to train the system. A persona represents the specific needs of many individuals for a particular scenario. This technique helps us develop initial robot behaviour adapted to user needs, and so reduces the amount of trials that participants have to perform during early stages of the system development. The paper describes how this behaviour model has been created and integrated into a functional architecture, and presents the motivation, background and conceptual framework for this new research direction. Future empirical studies will validate this approach and expand the initial definition of our model.**

I. INTRODUCTION

The understanding of how humans interact with robots in different environments is one of the main interests in the fiel of Human-Robot Interaction (HRI) [1]. The incorporation of social skills into robots' responses so as to achieve smoother interaction with humans remains a significan challenge. In our previous work (e.g. [2] [3] [4]) we tried to understand how people interact with robots in a domestic environment, and hence to develop robots which exhibit a greater awareness of context and users' needs when interacting with humans. The UH Robot House is the naturalistic environment used by our research group to perform a variety of HRI experiments that help us understand this interaction.

Fong et al. [5] assume that humans tend to interact with robots in ways that are similar to how they interact with other humans, i.e. people expect certain human-like social characteristics from robots. For instance, in the area of assistive robotics, where robots will become part of people's lives, social skills have to be incorporated in the interaction in order for the robots to be socially acceptable to their users. To achieve this, robot companions must be aware of the user's behaviour and activities they perform in their environment [6]. This helps robots respond appropriately to the user's actions during the interaction.

Nevertheless, we have to bear in mind some of the current problems pointed out in the literature concerning smart houses and HRI studies. Often a data-driven approach is being pursued, whereby a system collects data on people's behaviour and daily activities, identifying patterns that can be used to adapt the system to individual users. Recognizing typical user behaviours in a home setting usually requires large datasets to create accurate systems [7], and many difficultie could be found in recruiting participants for such experiments [8]. This point is particularly important when working with elderly people, who are one of the target user groups that our research is concerned with. Asking them to spend several days engaged in certain activities to generate training data for our system puts a huge burden on them. In order to avoid some of these issues, a knowledge-driven approach [9] [6] has been adopted which does not need to involve real users during the entire development process.

In this context, we have incorporated the Personas concept [10], into a Computational Behaviour Model for HRI in smart homes. This concept, extensively used in Human-Computer Interaction (HCI), provides us with a valuable set of 'pretend' user descriptions, which are used as guidelines during the definitio process of a system. Behaviour, attitudes and goals are examples of the characteristics define for each persona. This gives us the possibility of adapting the system and the robot companion's behaviour to the fina user through a persona matching process and just involving him/her during the evaluation process. In previous work on personas, many HCI projects used personas just as a guiding concept in the design phase of a system. Recently, a conceptual model of personas has been investigated in HCI applications [11] [12], however, to the best of our knowledge, the use of computational persona models to guide the behaviour of a companion robot in a domestic environment has not been attempted to date.

The remainder of this paper is organised as follows: Section II discusses related work. Section III presents the research questions and goals. In section IV, the methodology to be followed during the development process of the model is presented. Section V describes the Persona-Based Computational Behaviour Model. Finally, Section VI concludes the article.

II. RELATED WORK

HRI typically focuses on studying robotic systems that interact directly or indirectly with humans. The good understanding, evaluation and design of these systems can facilitate smooth and social interaction between robots and humans. Goodrich et al. [13] present a survey about current and historical HRI. Our HRI research is focused on the creation of social skills for robots during interaction with humans. In particular, we try to improve this interaction in a domestic environment where both human and robot share the same space.

A. Robot Companions in HRI

Being able to add the fl xibility and adaptability of human intelligence into robots' behaviour has become a major challenge for many researchers [1]. In HRI, researchers address robots endowed with social skills in order to improve interaction with users. The problem is that these skills cannot be achieved directly, typically a series of studies must be carried out in order to get an understanding on how to design the robot's social behaviour, e.g. [2] [3] [14]. For instance, the use of machine learning systems makes robots capable of providing more customized services as users interact with the system [15]. Nevertheless, this does not solve the problems pointed out in Section I, the recruitment of participants and the collection of large dataset in HRI studies. However, in a domestic setting, a priori knowledge of the user's characteristics and needs at home, which could be supplied by personas, allows us to develop a system capable of tackling the most common situations found in this kind of environments. Based on that assumption, we believe that the use of personas in HRI studies can help to defin the initial social skills and features needed during interaction.

B. Behaviour Models used in HRI

In the literature, several behaviour models are define as applied to intelligent agents, either robots or virtual agents. The majority of efforts are focused on developing models capable of achieving believability and empathy in agents in order to engage users during interaction. Dias et al. [16] built the Fatima behaviour model in which the agents' reasoning and behaviour are influence by their emotional state. The behaviour model is define through a set of goals, a set of emotional reactions rules, action tendencies and emotional threshold and decay based on the OCC (Ortony, Clore, & Collins) model of emotions [17]. This model was adapted and used during the LIREC project [18], in which the robot's behaviour was modifie based on the user's emotional parameters define in the system. Another example can be found in Tapus et al. [19]. The authors describe a behaviour model for assistive robots that modify their social interaction parameters according to the personality of post-stroke patients. Proxemics, speed and vocal content are all considered important robot characteristics, which can be varied so as to help patients improve their performance during certain tasks. In our approach, we would like to go a step further and develop a behaviour model with a larger number of variables in order to adapt the system to the variety of users' needs and preferences that can be found in a home environment.

C. The Concept of Personas

In 1999, Alan Cooper developed an alternative design technique called Goal-Directed Design [10]. With this technique, Cooper changed the previous User-Centred Design (UCD) philosophy that had been widely used in HCI. This new technique was based on understanding users' needs and goals, and definin design guidelines to adapt systems to those users. The fina target of each user using the system should be define precisely, but Cooper found some problems recruiting these users, i.e. volunteers to be involved during the whole design process. Without them, the definitio of their needs and goals could not be described. The alternative proposed by Cooper was to devise 'pretend' users called "Personas". According to Cooper, "Personas are not real people, but they represent them throughout the design process. They are hypothetical archetypes of actual users. Although they are imaginary, they are define with significan rigour and precision" [10]. Personas are considered a key component during the design process, focusing on them instead of any real user. Note, the more specifi the definitio of a persona is, the more useful it is as a design tool. Numerous studies demonstrate the usability of the Personas technique along the design process, e.g. [20] [21] [22].

D. Personas in HRI studies

The majority of research using personas can be found in the fiel of HCI, although a few studies have incorporated this technique to HRI. Ljungblad et al. [23] used personas as a means to describe people with interest in unconventional pets such as spiders or snakes, whose human-animal interaction is compared with current human-robot interaction. In a similar study, Ljunglblad et al. [24] used scenarios together with the Personas technique to design technological prototypes that consider the users' interests. Other related works are mainly based on the scenario-centred design technique, in which personas are considered part of the design process. Benyon et al. [25] used this technique to build companion technologies adapted to users' needs. Compagna et al. [26] suggest using a scenario-centred design in order to improve the development of mobile robot assistants used in care facilities. In our approach, personas will supply users' needs and characteristics that will influenc a robot companions' behaviour in a domestic environment. Thus, personas are not pure conceptual descriptions but are the key component of the robot's computational behaviour model and control architecture.

III. RESEARCH QUESTIONS AND GOALS

Focusing on the idea of achieving socially adaptive robot companions in living environments, we will assess whether the Personas technique, widely used in the HCI fiel [27], could be integrated into the development process of robot companions' behaviour adapted to users' needs. As a result, a computational behaviour model for robot companions has been define based upon this technique. During our research, several HRI studies will be necessary to defin and discover the extent to which this approach helps us solve some of the problems mentioned. The following questions will address the development process of our behaviour model:

- Which are the significan persona variables that must be included in the behaviour model, and that match users' preferences and needs using robot companions?
- What are the robot features that should be modifie in order to adapt the robot's behaviour?
- How will these features need to be modifie based on the persona variables defined

As stated before, a few HRI studies have used the Personas technique (see Section II), but none of them has related this technique specificall to robot companions in living environments. This technique supplies us with a set of users' goals and characteristics that defin users' requirements concerning the target system. In our case, robot companions living with user in the same house. Therefore, the creation of such a behaviour model will provide a HRI system with predefine robot behaviours adapted to different personas. Our research will evaluate how each user matches one of these personas define in the system, and at the same time, how each persona will affect the robot's behaviour based on its characteristics. This is hoped to result in acceptable robot behaviour while reducing the use of users during early stages of system development, and consequently, reducing the number of required HRI trials.

IV. DEVELOPMENT METHODOLOGY

In order to create the aforementioned behaviour model, an iterative methodology [28] [29] will be followed for the evaluation and development process. We will start with an initial two persona descriptions, define on the basis of previous HRI studies (see Section V). During the next stages, we will analyse, evaluate and modify the initial model and the personas defined based on the outcomes of future experiments. The methodology is depicted in Figure 1.

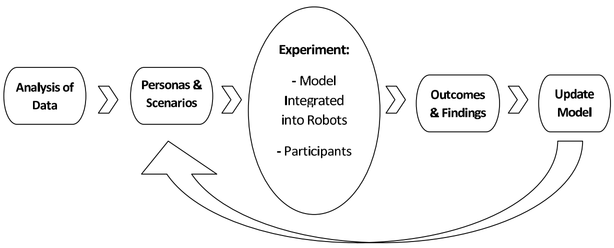

Fig. 1. Methodology Diagram

To the best of our knowledge, the explicit integration of personas in a computational behaviour model to affect robot's behaviour in domestic environments has not been done before. Therefore, the exact number of iterations for our iterative methodology cannot be define but has to be explored experimentally.

V. THE PERSONA-BASED COMPUTATIONAL BEHAVIOUR MODEL

A. Persona Definitio and Variables

As pointed out in the literature, each persona should be created based on studies with real users focusing on their goals [30]. The COGNIRION project [31], LIREC project [18] and our group's recent experiments in domestic settings [6], have helped us to develop this firs set of personas and the variables to represent them. Specificall , an HRI study by the team as part of the COGNIRON project [32], involved a sample of 28 adults with an even distribution in gender, aged between 20 and 55. This study's questionnaires were used to assess participants' opinions and preferences concerning companion robots' behaviour. Answers provided to questions such as *'Should the robot pay attention to what are you are doing'* or *'Should the robot try to fin out if you need help before it helps'*, supplied us with user information and preferences for a living environment with service robots.

More recently [6], we performed a two-session trial in which potential users in the Robot House were asked about their preferences for living with service robots. The main finding of these two studies regarding human behaviour and preferences in a HRI environment have helped us to defin two well-differentiated kinds of persona for our system. These personas will be used as a reference to modify robots' behaviour based on the persona's variables that are define below. However, during the next stages of our research, different experiments will be performed in order to evaluate, and then, modify this initial set of personas, their variables and how the robot's behaviour is modifie based on those variables. These most significan persona's variables, represented in italics, which depict each personas in our initial behaviour model, are the following:

- *Age, Gender, Educational Level, Technical Background* and *Computer Experience* are variables define as influentia in the way that users interact with technology and robots [14] [33] [34].
- *Previous Experience with Robots, Attitudes Towards Robots* and *Comfort with Robots* are pointed out in the literature as factors that tend to be associated with more negative evaluation of robots' behaviours [35].
- *User's Personality Traits*, acquired through the Big-Five Personality Test [36], are directly related to proxemics and expressiveness features of companions. Several studies can be found in the literature on this topic [37] [38].
- The *Robots' Role* how users perceive robots companions, can be considered influentia on different aspects of the robot's behaviour, see a recent paper by Koay et al. [39] has pointed out this finding
- *Index of Assistance Level* in ADLs. Robot companions should behave according to the level of assistance required by the user in each of the activities define for each environment. The index of assistance has been adapted from Katz et al. [40].
- *Proxemics's Preferences* including location, approach

direction and facing the user have been widely studied in the fiel of HRI [41] [4] [14]. These variables are key during human-robot interactions.

B. Usability Mechanisms

The model will adapt the robot's behaviour according to each persona's characteristics or variables. In order to achieve this, we have to defin which robot's features are going to be considered and how those will be modifie to adapt the robot's behaviour to the user, but bearing in mind the general purpose of the model. Therefore, the most common robot companions' features have been represented in the initial version of our computation model in order to facilitate its integration into similar environments. The mentioned variables are the following:

- Robot Interface
  - Font Size - Some user may require a bigger font size in the interface in order to facilitate interaction with the robot's touch screen
  - Interface and Feedback - The system will inform the user about each task completed. Inexperienced users will need to know the system status more frequently than experienced users.
  - Simple Interface - This option could use a simplifie version of the default interface. This could help certain users during their interaction with robots.
  - Warnings - The system should alert users though the robot's interface about unusual status of certain appliances, e.g. fridge door open or toaster on for a long period of time.
  - User Error Prevention - The system has to prevent input data errors. The generation of a clear and simple interface will allow us to achieve this purpose.
  - Verbal Communication - Robot companions could communicate the system status by voice responses, according to users' preferences.
- Proxemics Settings
  - Location (Personal or Social Zone) - The robot companion should stand in front of the user maintaining a personal or social distance depending on the user's characteristics.
  - Approach Direction (Front Left, Front or Front Right) - The robot will approach the user from the preferred direction.
  - Facing - The robot should turn its head in order to face the user during interaction.
- Assistance Level (High or Low) - The robot will offer help during users' activities at home. The frequency will depend on the individual user's needs. We will consider two levels of assistance, high and low. Intermediate levels have not been included at this stage, since we are looking for behaviour changes that are clearly distinguishable during human-robot interactions.
- Robot Expressiveness - The robot will show a different level of expressiveness depending on the user's personality. Two levels of expressiveness, High and Low, will be considered in our model.
- Robot Proactiveness - The robot will make its own decisions based on the status of the system. The level of proactiveness will depend on the user's characteristics. Once again, two level of proactiveness will be taken into account, High and Low, based on the previous reason.

The key point is the relation that we have created between the personas' variables and the robot's features, and how these features represent a particular robot's behaviour in the domestic environment. We have define a firs hypothesis based on the finding published by other researchers, i.e. the different HRI frameworks that can be found in the literature, and which give us clues about how each robot's feature could be affected by different persona variables. The correlation between features and variables will be precisely define and integrated into our behaviour model for robot companions. However, this initial correlation has to be tried and adjusted after the next set of studies, so no further information will be described in this paper.

Note, using two personas as a starting point will show whether users are able to detect differences in the robot's behaviour, based on two very different personas. This is just a starting point for developing more specifi and detailed persona models, but the initial results could provide a proof-of-concept.

C. MODEL INTEGRATION AND ARCHITECTURE

In this section, we will present our system architecture. Note, generalization and adaptability of the system are two key goals since we aim to facilitate its application across different environments and different robots.

As shown in Figure 2, we have define a centralised database system. The benefit of this approach are numerous: reliability, efficien y and scalability when dealing with large number of data and subsystems [42]. In addition, this architecture has also been adopted by the ACCOMPANY project [43] in order to perform studies with the Care-O-Bot 3 [44] and elderly people in living environments. The development of a similar architecture based on the same database, the same sensory network and the same robot connector interface, will allow us to move our system from one robot, Sunfl wer [1], to the other, Care-O-Bot 3, in later stages, in order to demonstrate the possibility of carrying out our studies with different companion robots. Below, we will explain the most important modules, their features and their internal operation. The main modules are the following:

- *Personas Module* - This module will be responsible for matching users and their characteristics with each persona of our system. Each participant will need to fil in a questionnaire through which this matching will be possible. The result together with the user preferences selected by participants will be stored in the database for later queries. During the course of our research the

[1] A mechanoid robot developed by Dr. Kheng Lee Koay as part of the LIREC project (http://www.lirec.org/). Sunfl wer is based on the "Pioneer" platform (Adept MobileRobots) with the addition of a head, a touch-screen user interface and diffuse LED display panels to provide expressive multi-coloured light signals to the user.

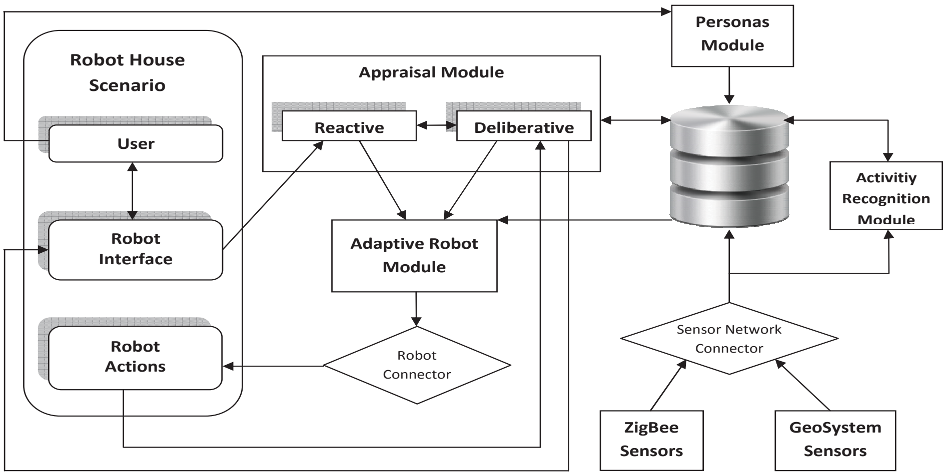

Fig. 2. Model Integration and Architecture

initial definitio of personas will be changed and the associated parameters adjusted.

- *Apprasial Module* - Following the approach used in the Fatima model [16], we have adopted the terms of *reactive* and *deliberative appraisal* in our system. The reactive component is responsible for executing the robot's actions selected by the user without the robot evaluating the contextual information, e.g. the user decides to send the robot to the charging place and the robot will execute this action. The deliberative component will evaluate each of the actions as well as the contextual information before sending the commands to the robot in order to adapt the robot's behaviour to the user's preferences and needs.
- *Adaptive Robot Module* - This module will be responsible for adapting the robot's operation to the characteristics of the persona. Before the system sends the instructions to the *Robot Connector*, the module will check on the database which Persona was matched with the user, and which parameters have to be sent to the robot in order to adapt its behaviour accordingly.
- *Robot Connector* - In order to move our system from one companion robot to another, we have to defin a connector per robot. Following this methodology, the system could be instantiated with a different companion without significan changes, just a new adapter has to be developed. These mechanisms make the system more versatile concerning changes.

VI. Conclusions and Future Work

The main goal of this article was to propose a different approach of using personas into the fiel of HRI. As a result a computational behaviour model for robot companions in domestic environments has been defined Personas have been used in HCI studies for the last ten years. We have tried to bear on this concept on HRI studies, and to develop a framework that allows the integration of personas as computational data structures in the robots' control architecture. The next step will be to evaluate and validate the model in a set of HRI studies in order to gather sufficien data and answer the research questions define in Section III. An iterative methodology (see Section IV) will be followed in order to improve the initial definitio of our model and to increase the number of personas define on the system.

Several problems were pointed out in Section I concerning HRI studies. From our point of view, the model and the methodology proposed cope with some of these issues directly, incorporating into robot companions the social skills expected by users during firs interactions. The presented Persona-Based Computational Behaviour Model will supply the system with a guideline to adapt the robots' behaviour to different users. Therefore, we expect that the use of this model minimizes the amount of trials that participants have to perform during early stages of the system development.

The behaviour model has been developed as a general purpose model for robot companions operating in similar contexts. Therefore, the model may potentially be used on similar robots and similar environments by other researchers. The further understanding of users' needs in domestic environments will lead us to build robot companions capable of interacting with users in a social way, and supporting them during their activities of daily living. Future experiments will validate and identify limitations of this approach, e.g. the extent to which it can generalize across different robot embodiments, environments and user groups.

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Appendix B

Sensor Network Description

B.1 Overview

This technical report was created in collaboration with Patrick Neuberger. It describes the wireless sensor network which has been installed in the Robot House. It is thought to be an extension of the already available GeoSystem (electric power consumption monitoring system) and comprises mainly sensors to detect open drawers and doors, occupied chairs/sofa seat-places and open water taps in the bathroom and kitchen sink. Also, a hand-held device was built that allows to segment the sensor data during an experiment by having the experimenter pressing one of its four buttons (up, down, left, right) at the specified time.

All those sensors are connected to a total of five ZigBee modules, which are spread across the Robot House's ground floor according to figure B.1.

The device named "XBee Gateway X4" forms the interface between the wireless ZigBee network and the wired Ethernet network and forwards the sensor readings to the network infrastructure for further processing. The hand-held device, which utilizes another ZigBee module, is not shown here.

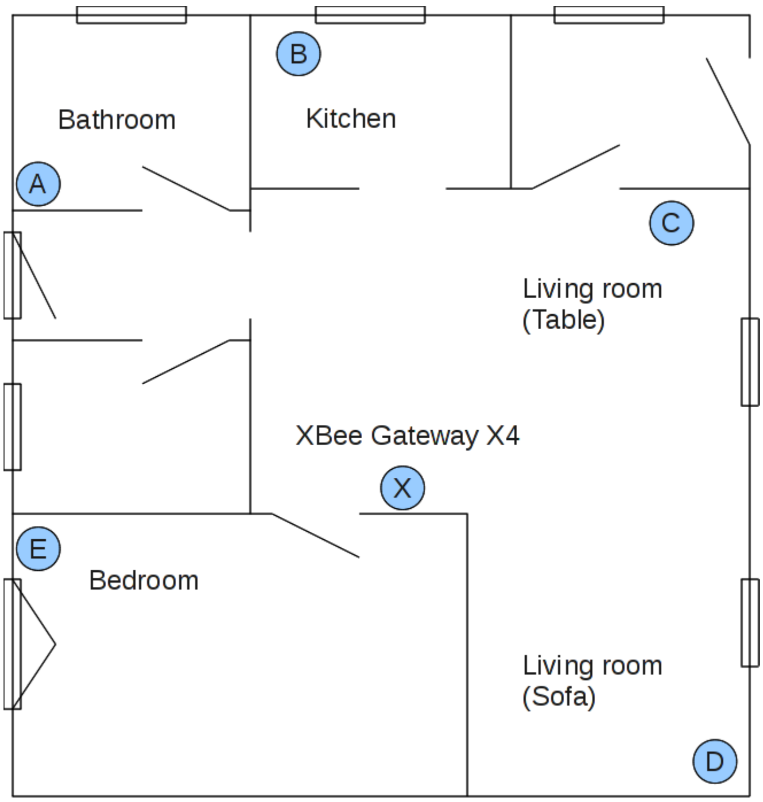

Figure B.1: Placement of the ZigBee modules in the Robot House

Currently the following sensors are being used:

- 26 reed contact pairs (Farnell # 101790) for the recognition of the state of all doors and drawers
- 4 temperature sensors Microchip MCP9700A for detecting the temperature of the cold and hot water pipes of the bathroom and kitchen sink
- 10 pressure mats Defender Security PM2/PK (size 720 x 390 mm^2) for detecting the usage of any chair or the sofa

B.2 Network Description

The wireless network currently comprises the following components, bought from the manufacturer Digi International Inc. (www.digi.com):

- Six XBee ZB embedded ZigBee modules with wire antenna (Manufacturer # XB24-Z7WIT-004)
- One ConnectPort X4 ZigBee to Ethernet gateway (Manufacturer # X4-Z11-E-W)

The decision for the system has been made by the following points:

- Due to their widespread usage and high-volume production, they provide good value for money in comparison with other, proprietary systems
- Unlike many competing systems, one ZigBee module comprises up to 11 (12) digital I/O lines, from which up to four can be used as single-ended analog inputs; this further improves the value for money massively
- ZigBee itself is a low-cost, low-power, wireless mesh networking standard with one focus on home automation and smart metering systems. The specification can be downloaded for non-commercial purposes for free at `http://www.zigbee.org`. Therefore a best possible security of investment in hardware components is given, in opposition to proprietary solutions which are typically bound to one single manufacturer. The advantage of mesh networks over standard point-to-point networks is seen in the better robutsness against disturbances and the higher transmission reliability.

- These modules are on the market for many years and it is a well-established solution. Furthermore the manufacturer provides different firmware solutions for the modules so that they can not only be used as ZigBee modules, but also for point-to-point connections etc.
- All components are readily programmed by the manufacturer, so the principal set-up of the wireless network can be limited to an absolute minimum. For the processing and transportation of the data, there exist different solutions:
  - The gateway possesses a Python[1] interpreter which can for example be used to collect the data and send it via the Ethernet port to a server.
  - For more complex processing tasks there also exists a Python software stack called iDigi DIA which allows the easy set-up of web pages containing the measurement values etc.

The biggest disadvantage of the ZigBee technology is that it operates in the 2.4 GHz frequency band, which is also usually being used by WiFi devices and microwave ovens. However, the advantages seem to outweigh this disadvantage; also so far there were no disturbances in either direction observed.

B.2.1 The ZigBee Gateway

B.2.1.1 Integration in the Ethernet infrastructure

The ZigBee gateway is connected to the Robot House's wired Ethernet infrastructure. Its current settings are:

```
IP address:  192.168.1.84      (obtained from the BT router via DHCP)
MAC address: 00:40:9D:3D:8B:BA
```

[1] Web site: `http://www.python.org`

A web-based configuration surface can be called when entering the gateway's IP address in a typical internet browser. Via this surface, not only the gateway, but also all ZigBee modules in reach of the wireless network can be configured. To prevent the system from accidental changes, the web surface access is protected with an username and a password.

B.2.1.2 Gateway Functionality

The gateway comprises a Python interpreter which allows for the greatest possible flexibility regarding the data transportation between the ZigBee and the Ethernet networks, the data manipulation/filtering and storage. Currently it runs a Python script that simply receives all data sent by the ZigBee modules, reformats it in a human-readable format and broadcasts it to the Ethernet on UDP port 5000.

The transmitted data looks approximately like this:

```
1291978993 [00:13:a2:00:40:32:de:87]! AD0 0.182
1291978993 [00:13:a2:00:40:32:de:87]! AD1 0.617
1291978993 [00:13:a2:00:40:32:de:87]! AD2 -
1291978993 [00:13:a2:00:40:32:de:87]! AD3 -
1291978993 [00:13:a2:00:40:32:de:87]! SUPPLY 0.746
1291978993 [00:13:a2:00:40:32:de:87]! DIO0 -
1291978993 [00:13:a2:00:40:32:de:87]! DIO1 -
1291978993 [00:13:a2:00:40:32:de:87]! DIO2 0
1291978993 [00:13:a2:00:40:32:de:87]! DIO3 1
1291978993 [00:13:a2:00:40:32:de:87]! DIO4 0
1291978993 [00:13:a2:00:40:32:de:87]! DIO5 1
```

```
1291978993 [00:13:a2:00:40:32:de:87]! DIO7 0

1291978993 [00:13:a2:00:40:32:de:87]! DIO10 0

1291978993 [00:13:a2:00:40:32:de:87]! DIO11 1

1291978993 [00:13:a2:00:40:32:de:87]! DIO12 1
```

I. e. each data set, representing one channel's status, consists of four space-separated entries and is terminated with a line break character. The four entries' meanings are (from left to right):

- Timestamp (whole seconds). Beware: This "timestamp" represents the seconds that passed since the last gateway start-up.
- The transmitting XBee module's MAC address
- The channel name. Possible values:
  - AD0 – AD3 (analog channels)
  - SUPPLY (analog channel)
  - DIO0 – DIO7 (digital channels)
  - DIO10 – DIO12 (digital channels)
- The channel value. Analog channels transmit a float value representing the input voltage in volts; the valid range reaches from 0 to 1.215. Digital channels transmit either 0 or 1. If the channel is not active, "-" will be transmitted. If the XBee module is configured for example to have only digital inputs, the channels AD0 – AD3 will always deliver "-". Also the channel "SUPPLY" is not active with the current XBee module configuration.

A Python script called udptestreceiver.py is available which simply receives all UDP broadcast messages and writes them to the console.

B.2.2 The ZigBee Modules

B.2.2.1 Pin Connections

Figure B.2 depicts – according to the module datasheet – the pin positions of one XBee module, and table B.1 explains the pin assignments.

Input pins are either used as digital inputs with integrated pull-up resistor when connected to reed contacts or pressure mats, or as analog inputs without integrated pull-up resistor when connected to temperature sensors.

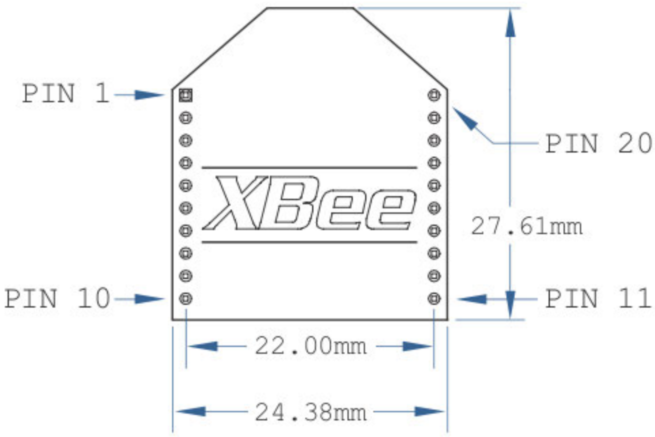

Figure B.2: XBee module pin positions (Top view)

It was found that for some reason the pull-up resistors located on the inputs DIO6 and DIO7 are not functioning as intended. Currently these channels are only used in the "Living room (Table)" device, on which external pull-up resistors of $30k\Omega$ were installed on these port pins.

Table B.1: XBee module pin assignments

Pin #	Name	Function
1	VCC	Power supply: +
2	DOUT	
3	DIN / CONFIG	
4	DIO12	Digital input
5	RESET	
6	RSSI PWM / DIO10	Digital input
7	DIO11	Digital input
8	(reserved)	
9	DTR / SLEEP_RQ / DIO8	Digital input
10	GND	Power supply: Ground
11	DIO4	Digital input
12	CTS / DIO7	Digital input
13	ON / SLEEP	
14	VREF	
15	Associate / DIO5	Digital input
16	RTS / DIO6	Digital input
17	AD3 / DIO3	Analog / digital input
18	AD2 / DIO2	Analog / digital input
19	AD1 / DIO1	Analog / digital input
20	AD0 / DIO0 / Button	Analog / digital input

B.2.2.2 Power Supply

The selected ZigBee modules can be operated in a voltage range of 2.1 to 3.6VDC. For cost reasons and due to the fact that the devices are mostly run in short-term applications (i. e. it is expected that no experiment takes longer than four weeks), each module is powered by two alkaline AA size batteries, connected in series. Furthermore, the supply voltage is buffered with a $1\mu F$ ceramic multi-layer capacitor placed near the supply voltage pins of the ZigBee module. Since the modules have a current consumption not higher than 45mA typically, it is expected that the alkaline battery cells can be emptied by approximately 70 percent before the cell voltage drops below 1.1V. Furthermore, the module-to-module distance is in every case smaller than 10 meters, and in most cases two devices are separated by only one wall. Thus it is expected that the ZigBee modules can operated for a relatively long time from one set of batteries.

If this voltage is insufficient, a voltage regulator must be used. However, even the most modern ultra-low-drop linear voltage regulators need a quiescent current of at least 5 to $10\mu A$, which is much more than the module's power-down power consumption ($< 1\mu A$). Switching regulators are even worse.

B.2.2.3 Reed Contact and Pressure Mat Connections

Since the deployed reed contact and pressure mat sensors contain simple binary switches, they are connected between GND and the according digital input. By programming the XBee module accordingly, a pull-up resistor of approximately $30k\Omega$ is enabled on the digital input. So, the input delivers a "0" value if the contact is closed (i. e. a magnet is nearby the reed contact sensor or pressure is applied onto a pressure mat) and "1" otherwise.

B.2.2.4 Temperature Sensor Connections

The used temperature sensor MCP9700A provides an accuracy of $\pm 2°C$ in the range of $0°C$ to $70°C$, functions with a supply voltage of at least 2.3V and typically draws $6\mu A$. The analog output voltage changes linearly with $10.0\frac{mV}{°C}$, yielding 500mV at $0°C$ and 1500mV at $100°C$. The ZigBee module's analog input can measure voltages between 0 and 1200mV; this relates to a temperature range of $-40°C$ (sensor's specified minimum temperature) to $+70°C$ and should be very sufficient for the planned area of use (measuring water tap temperature).

Also the sensor is capable of driving relatively high capacitive loads (factory tested with 1nF), thus making it ideal for this application in which the sensor is connected to the measuring input via an up to five meters long cable. For the first tests the TO-92 package variant was chosen because it allowed for a simply solder connection with the sensor cable and the sensor could simply be tied to the water pipes using adhesive tape. This sensor is also available in the SMT package variants SOT-23 and SC-70 which provide a better thermal response but are much worse to handle if not soldered to a PCB.

The decoupling of the supply voltage happened by soldering a SMT size 0805 100nF ceramic multi-layer capacitor between the supply voltage pins near the temperature sensor. Currently the temperature sensors are connected directly to the analog inputs. It was found that for the short cable lengths to the temperature sensors as used by now, the transmission happens without mentionable disturbances, i. e. the measurements proved to be surprisingly stable. When using longer cables, it could however be necessary to use a R-C low pass filter near the measuring input, consisting for example of a resistor of $1k\Omega$ and a capacitor of 100nF and thus forming a limiting frequency of 1.6 kHz, for buffering and stabilizing the analog voltage. The influence of the measuring input can be neglected in this case because the module's input resistance is better than $1M\Omega$ (according to the datasheet).

B.2.2.5 Firmware Configuration

The XBee modules are configured so that they sample their inputs and transmit the results to the gateway every two seconds.

The exact module configuration register contents (for example accessible via the ZigBee gateway web surface under "XBee network" → (XBee module of choice) → "Advanced settings") are displayed in table B.2.

Note: With these settings, all inputs are sampled as digital inputs with pull-up resistors enabled and the data is transmitted to the ZigBee gateway with the MAC address 00:13:A2:00:40:32:CC:35 (Beware: Do not mix up with the gateway's Ethernet MAC address!). In order to use the inputs 0 and 1 as analog inputs without pull-up resistor, the changes shown in table B.3 have to be made.

B.3 System Deployment

B.3.1 ZigBee Sensor Deployment

In table B.4 an overview over the deployed sensors within the ZigBee network as much as their connection to the relating ZigBee module is given.

Typically, closed doors/drawers (i. e. the magnet of the reed contact pair is in immediate neath of the reed contact sensor) generate a "0" value, since the closed reed contact pulls the pin to "Low" level (Ground). Not occupied pressure mats however deliver a "1", since the contact closes if someone sits or stays on them.

Table B.5 shows the MAC addresses of the XBee modules currently deployed.

Table B.2: XBee module configuration settings

Register	Value	Register	Value
DH	0x0013A200	GT	1000
DL	0x4032CC35	NJ	255
ST	5	JN	0
SO	0	JV	0
SN	1	KY	(empty)
SP	200	NH	30
D0 – D7	3	NW	0
P0 – P2	3	NI	(desired name)
IR	50	RO	3
PR	0x3FFF	PL	4
IC	0x0	PM	1
AR	255	RP	40
LT	0	SC	0x1FFE
BH	0	SD	3
CC	+	NB	0
CI	0x11	BD	3
CT	100	SN	1
DE	0xE8	SM	4
NT	60	SE	0xE8
EE	0	ZS	0
EO	0x0	V+	0
ID	0x0000000...		

Table B.3: XBee module configuration changes for analog inputs

Register	Value
PR	0x3FE7
D0 – D1	2

B.3.2 GeoSystem Sensor Deployment

In table B.6 an overview about the GeoSystem sensor devices is given.

B.4 System Notes

B.4.1 Sensor State Processing

This step is intended to deduce the supervised device's states from the measured values. It is primarily used to estimate the water tap state from the water pipe temperatures and the states of electrical devices from their power consumptions.

To deduce the "water flow state" (i. e. water tap open/closed) from the cold and hot water pipe temperature, respectively, the following algorithm is being used:

- Exercise an average filter over the last 5 temperature sensor values
- If the latest sensor value for cold water is less than 90%, or greater than 110% in the case of the hot water, the average value calculated and the state was "close", the state is set to "open"
- If the latest sensor value was "open" and the cold water is greater than 110%, or just lower than the average value, in the case of the hot water, the current water tap state is set to "closed".

ID	Device	Channel	Sensor Type	Description
1	Kitchen	AD0	Temperature	Water Pipe Sink Hot
2	Kitchen	AD1	Temperature	Water Pipe Sink Cold
3	Kitchen	DIO2	Reed contact	Ceiling cupboard door left
4	Kitchen	DIO3	Reed contact	Ceiling cupboard door middle
5	Kitchen	DIO4	Reed contact	Ceiling cupboard door right
6	Kitchen	DIO5	Reed contact	Floor cupboard drawer middle
7	Kitchen	DIO11	Reed contact	Floor cupboard drawer right
8	Kitchen	DIO7	Reed contact	Floor cupboard door middle
9	Kitchen	DIO12	Reed contact	Floor cupboard door right
10	Kitchen	DIO10	Reed contact	Floor cupboard door left
11	Bathroom	AD0	Temperature	Water Pipe Sink Hot
12	Bathroom	AD1	Temperature	Water Pipe Sink Cold
13	Bathroom	DIO2	Reed contact	Bathroom door
14	Bathroom	DIO3	Reed contact	Toilet flush
15	Living room (sofa)	DIO0	Pressure mat	Sofa seatplace #0
16	Living room (sofa)	DIO1	Pressure mat	Sofa seatplace #1
17	Living room (sofa)	DIO2	Pressure mat	Sofa seatplace #2
18	Living room (sofa)	DIO3	Pressure mat	Sofa seatplace #3
19	Living room (sofa)	DIO4	Pressure mat	Sofa seatplace #4
20	Living room (table)	DIO0	Pressure mat	Table seatplace #0
21	Living room (table)	DIO1	Pressure mat	Table seatplace #1
22	Living room (table)	DIO2	Pressure mat	Table seatplace #2
24	Living room (table)	DIO4	Reed contact	Living room door

25	Living room (table)	DIO5	Reed contact	Cupboard big drawer bottom
26	Living room (table)	DIO3	Reed contact	Cupboard big drawer top
27	Living room (table)	DIO7	Reed contact	Cupboard small door left
28	Living room (table)	DIO6	Reed contact	Cupboard small door right
29	Living room (table)	DIO10	Reed contact	Cupboard small drawer bottom
30	Living room (table)	DIO11	Reed contact	Cupboard small drawer middle
31	Living room (table)	DIO12	Reed contact	Cupboard small drawer top
32	Bedroom	DIO0	Reed contact	Desk drawer bottom
33	Bedroom	DIO1	Reed contact	Desk drawer middle
34	Bedroom	DIO2	Reed contact	Desk drawer top
35	Bedroom	DIO3	Reed contact	Desk door
36	Bedroom	DIO4	Pressure mat	Office chair
37	Bedroom	DIO5	Reed contact	Bedroom door
39	Bedroom	DIO7	Pressure mat	Bed contact
41	Bedroom	DIO10	Reed contact	Wardrobe door left
42	Bedroom	DIO11	Reed contact	Wardrobe door middle
43	Bedroom	DIO12	Reed contact	Wardrobe door right

Table B.4: ZigBee sensor deployment

Table B.5: MAC addresses of the XBee modules currently used

XBee module	MAC address
Kitchen	[00:13:a2:00:40:32:de:87]!
Bathroom	[00:13:a2:00:40:62:a9:52]!
Bedroom	[00:13:a2:00:40:62:a9:4f]!
Living room (Sofa)	[00:13:a2:00:40:62:a9:4d]!
Living room (Table)	[00:13:a2:00:40:62:a9:4e]!

Regarding the reed contact sensors, typically installed in doors, cupboard or drawers, these generate a "0", since the closed reed contact pulls the pin to "Low" level (I. e. the magnet of the reed contact pair is in immediate beneath of the reed contact sensor). On the other hand, not occupied pressure mats however deliver a "1", since the contact closes if someone sits or stays on them.

For the GeoSystem devices a simple power limit can be introduced to tell if a device is switched on or off, although some devices (e. g. the fridge) need a slightly more complex logic when inferring its status.

B.4.2 Usage Description

A brief ZigBee sensor network usage description is included in this section. In order to configure and start using the network installed in the UH Robot House, the following actions must be executed. More details about the MySQL tables, source code and scripts created can be found in the GitHub repositories (*Thesis Software Modules - GitHub* 2016):

- Power on the ConnectPort X4 Gateway and connect it to the Ethernet

Table B.6: GeoSystem sensor deployment

ID	Room	GeoSystem ID	Description
44	Other	1	Lights exterior
45	Other	2	Upstairs lights
46	Other	3	Downstairs lights
47	Kitchen	7	Cooker
48	Other	8	Garage
49	Other	9	Sockets
50	Other	10	Sockets ext. and garden
51	Other	12	Mains supply
52	Living room (sofa)	13	TV
53	Kitchen	14	Fridge / Freezer
54	Kitchen	15	Kettle
55	Bedroom	16	Computer
56	Bedroom	17	Table lamp
57	Kitchen	18	Microwave
58	Kitchen	19	Dishwasher
59	Kitchen	20	Toaster
60	Living room (sofa)	21	Living room light
61	Other	22	Roomba
62	Other	24	Doorbell

- Power on all XBee modules (i.e. installing batteries for each battery holder)

Then the gateway should start immediately to broadcast all received ZigBee messages to the Ethernet. To use the Robot House ARS software, the following steps must be taken:

- Set up a MySQL table with the following columns: timestamp (longint), module (string), id (int), room (string), channel (string), name (string), value (string), status (string) (Note: The contents of column "id" are not unique; instead it contains the sensor's ID according to the tables above.)
- Edit the sensorsdata.xml (sensors' information) and config.properties (configuration variables) files accordingly
- Execute SensorNetworkInterface.jar, depending on the system through double click or using the next command line: java -jar SensorNetworkInterface.jar
- Point a web browser to `http://localhost:81`

In order to test the software with the ZigBee sensor network, a Python script called "udptestbroadcast.py" is available to run. This script simulates the ZigBee gateway by simply broadcasting random values on all channels of pre-defined ZigBee devices. If either of two sensor networks installed is not available, we can disable it from the interface, in order to avoid errors during establishing a connection. For that, we just need to modify the value of "GEO_AVAILABLE" or "ZIGBEE_AVAILABLE" variables to *False* on the *config.properties* file. This file is used to set the connection parameters for each sensor network apart from other parameters that are explained in the document itself. The configuration file is specified as follows (see Code B.1):

Code B.1: Sensor Network Configuration File

```
# The port on which the program is listening for UDP broadcast messages
# transmitted by the ZigBee gateway
PORT=5000

# If some of the sensor networks are not available we can turn it off in
# the interface, in order not to produce errors during the connection
GEO_AVAILABLE=false
ZIGBEE_AVAILABLE=true

# The settings of the Geo-System MySQL server / database / table
MYSQL_GEO_SERVER=<ip_address>
MYSQL_GEO_USER=guest
MYSQL_GEO_PASSWORD=<password>
MYSQL_GEO_DB=livewiredb
MYSQL_GEO_QUERY=CALL expPower

# The settings for the channel logging MySQL server / database / table
MYSQL_LOG_SERVER=localhost
MYSQL_LOG_USER=root
MYSQL_LOG_PASSWORD=<password>
MYSQL_LOG_DB=livewiredb

# table fields: timestamp (longint), id (int), room (string), channel (string),
# name (string), value (string), status (string)
MYSQL_LOG_TABLE=logging
MYSQL_LOG_COLUMNS=(timestamp,module,id,room,channel,name,value,status)

# Sensors File path
SENSORS_XML_FILE=sensorsdata.xml
ACTIVITIES_XML_FILE=activitiesdata.xml

Logs Folder
LOGS_FOLDER=Experiments/

#Number Format (Uk format 0.000 / European format 0,000)
NUMBER_FORMAT=0.000

#They are the columns whose values can be obtained from the sensors
MODULE_COLUMN=Module
CHANNEL_COLUMN=Device
ID_COLUMN=ID
NAME_COLUMN=Description
TYPE_COLUMN=Type
VALUE_COLUMN=Value
STATUS_COLUMN=Status
```

Appendix C

Demographic and Forms

C.1 Experiment 1 - Consent Form and Questionnaire

High-Level Activity Recognition in a Smart House study

Section 1: Information about the research and the experiment

In the future, robot companions could support us with our activities of daily life (ADL). In order to make this possible, we need to make them aware about the changes in the environment in which they will be taking part. For this reason, our houses should be prepared to supply the data that allows robots to make the appropriate decisions.

Pursuing this idea, an activity recognizer system has been installed in the ‘Robot House’. The system is based on a sensor network and an application to manage the data stream every second. This experiment is trying to *measure the accuracy of this activity recognizer system* and the participants just need to behave as they would behave in their own house. You will be asked to perform certain daily living tasks at home. Two sessions will be required and the length of each session will be approximately 20 minutes plus an introductory part (10 minutes) in which you will familiarize yourself with the layout and facilities of the house.

This research will involve some questionnaires and collection of video material required for the analysis of the experiments. All data collected on individual participants will be treated with full confidentiality. At no time throughout the whole course of the research project will your name or any other personal details that you provide be identifiable, (i.e. your name will not appear in any internal or external publications). All evaluation work will be based on the participant numbers allocated to each subject. This ID code will form the basis of our evaluations, not your real name.

Participation in this study is entirely voluntary. If at any point you do not wish to continue with the study, you may withdraw, this will not reflect badly on you. The questionnaires provided do not have any right or wrong answers, nor should they be viewed as tests. However, you can decide not to answer certain questions in the questionnaires if you do not wish to.

Section 2: Consent to take part in the trials

Name of Researchers: Prof. Kerstin Dautenhahn, Dr. Kheng Lee Koay, Ismael Duque

(PLEASE INITIAL BOXES)

I CONFIRM THAT I HAVE READ AND FULLY UNDERSTOOD THE INFORMATION PROVIDED FOR THE ABOVE STUDY. I UNDERSTAND THAT MY PARTICIPATION IS VOLUNTARY AND THAT I AM FREE TO WITHDRAW AT ANY TIME, WITHOUT GIVING ANY REASON. I AGREE TO TAKE PART IN THE ABOVE STUDY. ☐

WE WOULD LIKE TO USE SOME OF THE VIDEO FOOTAGE FOR FUTURE CONFERENCES AND PUBLICATIONS. I CONSENT TO MY VIDEO FOOTAGE RECORDED DURING THE EXPERIMENTS TO BE USED FOR THIS PURPOSE. ☐

ID Number: User-☐☐☐

Name of participant: ______________________________

Signature: ______________________________

Date: ______________________________

If you have any questions regarding the above study, please contact the experimenter:

Ismael Duque – ismaelduquegarcia@gmail.com

Thank you.

Section 3: About You

Thank you for your time, we would be grateful if you could complete the questions below:

1. Age: ☐☐

2. Gender: Male ☐ Female ☐

3. Occupation or course if you are a student: ……………………………………………………

4. Nationality…………………………………………………………………………………….

5. Handedness: left-handed ☐ right-handed ☐ either ☐

6. Have you ever been in the Robot House before for other kind of experiments?

   Yes ☐ No ☐

7. May we contact you to participate in similar studies in the future? If so, please provide contact information (email address or phone number):

   ....

Section 4: Questionnaire Session 1

1. Please give us your opinion about the following questions:

   a) How did you find the scenarios on home activities?

1	2	3	4	5
Very natural	Quite natural	Neutral	Quite unnatural	Very unnatural

   b) Did you carry out the activities in the same way in which you behave usually in your own house/flat?

1	2	3	4	5
Very similar	Quite similar	Neutral	Quite different	Very different

2. If this were your living room, what other additional activities would you carry out in this environment?

   ....

   ....

3. If this were your kitchen, what other additional activities would you carry out in this environment?

   ....

   ....

4. Additional comments or suggestions:

   ....

   ....

   ....

   ....

   ....

Section 5: Questionnaire Session 2

1. Please give us your opinion about the following questions:

   a) How did you find the scenarios on home activities?

1	2	3	4	5
Very natural	Quite natural	Neutral	Quite unnatural	Very unnatural

   b) Did you carry out the activities in the same way in which you behave usually in your own house/flat?

1	2	3	4	5
Very similar	Quite similar	Neutral	Quite different	Very different

2. If money was of no concern, and you could afford to buy a robot for your home, would you be interested in buying one for helping you with the activities of daily life that were shown along this experiment?

   Yes ☐ No ☐

3. If yes, which kind of tasks would you want the robot to help you in?

   ....

   ....

4. Additional comments or suggestions:

   ....

   ....

   ....

   ....

   ....

ID Number: User-__ __ __

Activities Script - First session

- Could you watch some video on the television? (2 minutes)
  - ☐ Sitting_Living_Room
  - ☐ TV_ON
  - ☐ Watching_TV
- Could you prepare some breakfast for yourself? (5 minutes)
  - ☐ Using_Toaster
  - ☐ Using_Kettle
  - ☐ Preparing_Food
  - ☐ Preparing_Cold_Drink
  - ☐ Preparing_Hot_Drink
- Could you lay the table? (2 minutes)
  - ☐ Laying the table
- Could you have your breakfast in the living room? (5 minutes)
  - ☐ Having_Meal
  - ☐ Sitting_Living_Room
- Could you clean the table and put your plate back in the kitchen? (1 minutes)
  - ☐ Cleaning_Table
- Could you take a magazine or newspaper and going to the sofa? (2 minutes)
  - ☐ Spare_Time_Living_Room
- Could you switch on the computer and have a look to any website that you wish? (2 minutes)
  - ☐ Computer_ON
  - ☐ Sitting_Dining_Area
  - ☐ Using_Computer_Dining_Area

C.2 TIPI Questionnaire

Here are a number of personality traits that may or may not apply to you. Please write a number next to each statement to indicate the extent to which you agree or disagree with that statement. You should rate the extent to which the pair of traits applies to you, even if one characteristic applies more strongly than the other:

	Disagree strongly	Disagree moderately	Disagree a little	Neither agree nor disagree	Agree a little	Agree moderately	Agree strongly
Extraverted, enthusiastic							
Critical, quarrelsome							
Dependable, self-disciplined							
Anxious, easily upset							
Open to new experiences, complex							
Reserved, quiet							
Sympathetic, warm							
Disorganized, careless							
Calm, emotionally stable							
Conventional, uncreative							

Table C.1: The TIPI (Ten-Item Personality Inventory) questionnaire used during the HRI experiments

C.3 Personas Experiments - Pre-Experiment Introduction

The following introduction was read to the participants prior to the *Experiment 2* and the *Experiment 3* in order to give more information about the house, facilities and the robot companion to interact with (Sunflower). The introduction stated as follows:

Welcome to the UH Robot House. The main purpose for you today is to interact with a robot companion at this house through a set of pre-defined scenarios and tasks. The main areas where the experiment will take place are the kitchen, hall, dining area and living room (the researcher points to each room as they are mentioned). The majority of cupboards in the facilities are labelled with their content so you could quickly find any utensil or object if requested or needed. Sunflower, will be the robot used to performed this experiment (The robot is pointed as mentioned). This robot is able to locate you around the main areas of the house, capable of reminding you tasks and carry objects around the house areas. Its capabilities are the followings: moving around the facilities using its mobile base, open the its tray to transport objects around the house, moving its head and its torso to catch your attention, flashing its upper-torso light to indicates movement(yellow), catch attention (blue or pink), indicated position reached (green). In addition, there is a touch screen tablet in front of its tray to inform at any time about the current task status. This tablet is used to command the robot or reply to its question too using a simple and intuitive interface. The robot is able to talk to you through its speaker, but there is not voice recognition installed so the only way to command it is through the interface shown *on the tablet. You will be guide for the researcher (myself) through the experiment and receive all the convenience instructions at the required time. The duration of the experiment could take up to 1 hour and it is totally voluntary to complete it, so please feel free to stop the experiment at any time if needed. I would like you to act naturally, as you were in your own house, and pay attention to the robot when interacting with you as some questions would be asked about its behaviour during the course of the experiment. Thanks for taking part in this experiment and helping me with my research. I hope you enjoy the experience.*

C.4 Personas Experiments - Pre-Experiment Questionnaire

1. How old are you?
   (a) Under 30
   (b) 30-45
   (c) 46-60
   (d) Over 60
2. What is your gender?
   (a) Female
   (b) Male
3. What is your education level?
   (a) No high school diploma
   (b) High school diploma
   (c) 2-year degree
   (d) 4-year degree
   (e) Postgraduate degree
4. What is your profession or field of study? (Open field)
5. Do you use computer technologies (e.g. computer/table/smartphone) as part of your daily life?
   (a) Yes - Number of hours per day:

(b) No

6. If yes, what do you use these technologies for? (Choose as many as you wish)

   (a) Browsing and emailing

   (b) Social networking (Facebook, Skype, etc)

   (c) Work / School work

   (d) Music and films

   (e) Video games

   (f) Others (Please specify which):

7. TIPI Questionnaire - See Section C.2

8. Do you have previous experience interacting with robot companions?

   (a) None

   (b) Rarely

   (c) Occasionally

   (d) Often

9. How would you describe your attitude towards robots?

   (a) Cautious

   (b) Indefferent

   (c) Curious

   (d) Other:

10. How comfortable would you feel when...

   (a) Being approached by a robot

    i. Very Uncomfortable
    ii. Uncomfortable
    iii. Neutral
    iv. Comfortable
    v. Very Comfortable

(b) Being physically close to a robot

    i. Very Uncomfortable
    ii. Uncomfortable
    iii. Neutral
    iv. Comfortable
    v. Very Comfortable

(c) Moving in the same room as a robot

    i. Very Uncomfortable
    ii. Uncomfortable
    iii. Neutral
    iv. Comfortable
    v. Very Comfortable

11. How would you like to interact with the robot?

(a) As a friend

    i. Completely Disagree
    ii. Disagree
    iii. Neutral
    iv. Agree

v. Completely Agree

(b) As a servant

i. Completely Disagree

ii. Disagree

iii. Neutral

iv. Agree

v. Completely Agree

(c) As a collegue

i. Completely Disagree

ii. Disagree

iii. Neutral

iv. Agree

v. Completely Agree

(d) As a pet

i. Completely Disagree

ii. Disagree

iii. Neutral

iv. Agree

v. Completely Agree

(e) As a tool

i. Completely Disagree

ii. Disagree

iii. Neutral

iv. Agree

v. Completely Agree

12. What kind of robot assistance level or company level (i.e. the robot providing social company by staying close etc.) would you prefer during the following activities of your daily life?

    (a) Watching Television

        i. Low

        ii. Medium

        iii. High

    (b) Using the Computer

        i. Low

        ii. Medium

        iii. High

    (c) Reading or Playing Video Games

        i. Low

        ii. Medium

        iii. High

    (d) Preparing Food

        i. Low

        ii. Medium

        iii. High

    (e) Preparing a Drink

        i. Low

ii. Medium

iii. High

(f) Having a Meal

i. Low

ii. Medium

iii. High

(g) Laying the Table

i. Low

ii. Medium

iii. High

(h) Cleaning the Table

i. Low

ii. Medium

iii. High

(i) Alert to Doorbell Sound

i. Low

ii. Medium

iii. High

(j) Reminder Tasks (e.g. appointments, taking medicine)

i. Low

ii. Medium

iii. High

13. What distance would you prefer to keep between you and the robot when interacting?
    (a) Personal Zone (0.45 to 1.2m)
    (b) Social Zone (1.2 to 3.6m)
    (c) Over 3.6m
14. Which of these robot approach directions would you prefer during the interaction?
    (a) Front-Left
    (b) Front
    (c) Front-Right
15. (Introduced for the Experiment 3) Which level of expressiveness would you prefer the robot to have during the interaction?
    (a) Low
    (b) Medium
    (c) High
16. (Introduced for the Experiment 3) Which level of proactiveness would you prefer the robot to have during the interaction?
    (a) Low
    (b) Medium
    (c) High

17. (Introduced for the Experiment 3) Could you indicate the degre in which you would accept the robot to interrupt you during your activities of daily living (e.g. reading or listening to music)?

    (a) Low

    (b) Medium

    (c) High

C.5 Experiment 2 - Consent Form and Questionnaire

ID Number: User-____

Human-Robot Interaction Study with Sunflower

Section 1: Information about the research and the experiment

In the future, robot companions could support us with our activities of daily life (ADL) at home. In order to make this possible, they have to be aware of the environment and the user's characteristics and needs. The aim is to create mechanisms that allow us to develop initial robot behaviour, i.e. behaviour when first encountering the user, which is already adapted to each user without the necessity of collecting in advance a large dataset to train the system.

The incorporation of social skills into robots' responses so as to achieve smoother interaction with humans remains a significant challenge. In our previous work, we have tried to understand how people interact with robots in a domestic environment, and hence to develop robots which exhibit a greater awareness of context when interacting with humans. The UH Robot House is the naturalistic environment used by our research group to perform a variety of HRI experiments that help us understand this interaction.

In this new experiment, we will carry out a set of human-robot interaction studies to find out what are your preferences and needs as a user when interacting with a robot at home. You will be required to behave as you would behave in your own house and without any kind of pressure, as you are not going to be evaluated. You will be asked to perform certain tasks with the robot, and then, mark your preferences in a simple questionnaire. Just one session will be required and its length will be approximately 1 hour during which you will have time to familiarize yourself with the system and facilities of the house.

This research will involve some questionnaires and collection of video/audio material required for the analysis of the experiments followed by an interview. All data collected on individual participants will be treated with full confidentiality. At no time throughout the whole course of the research project will your name or any other personal details that you provide be identifiable, (i.e. your name will not appear in any internal or external publications). All evaluation work will be based on the participant numbers allocated to each subject. This ID code will form the basis of our evaluations, not your real name.

Participation in this study is entirely voluntary. If at any point you do not wish to continue with the study, you may withdraw, this will not reflect badly on you. The questionnaires provided do not have any right or wrong answers, nor should they be viewed as tests. However, you can decide not to answer certain questions in the questionnaires if you do not wish to.

This study was approved by the UH Ethics Committee under protocol number 1213/13

Section 2: Consent to take part in the trials

Name of Researchers: Prof. Kerstin Dautenhahn, Dr. Kheng Lee Koay, Ismael Duque

I CONFIRM THAT I HAVE READ AND FULLY UNDERSTOOD THE INFORMATION PROVIDED FOR THE ABOVE STUDY. I UNDERSTAND THAT MY PARTICIPATION IS VOLUNTARY AND THAT I AM FREE TO WITHDRAW AT ANY TIME, WITHOUT GIVING ANY REASON. I AGREE TO TAKE PART IN THE ABOVE STUDY. ☐

WE WOULD LIKE TO USE SOME OF THE VIDEO FOOTAGE OR AUDIO RECORDED FOR FUTURE CONFERENCES AND PUBLICATIONS. I CONSENT TO MY VIDEO FOOTAGE OR AUDIO RECORDED DURING THE EXPERIMENTS TO BE USED FOR THIS PURPOSE. ☐

ID Number: User-☐☐☐

Name of participant: ______________________________

Signature: ______________________________

Date: ______________________________

If you have any questions regarding the above study, please contact the experimenter:

Ismael Duque – ismaelduquegarcia@gmail.com

Thank you.

ID Number: User-____

Scenarios & Questionnaire

Interface and Communication

Interface –Condition 1

How is this interface adapted to your preferences?

Not adjusted at all	Not adjusted	Neutral	Quite adjusted	Very adjusted

Robot's Voice

Yes ☐

No ☐

Interface – Condition 2

How is this interface adapted to your preferences?

Not adjusted at all	Not adjusted	Neutral	Quite adjusted	Very adjusted

Location and Approach

Location – Condition 1

How comfortable did you feel in front of the robot?

Not comfortable at all	Not comfortable	Neutral	Quite comfortable	Very comfortable

Location – Condition 2

How comfortable did you feel in front of the robot?

Not comfortable at all	Not comfortable	Neutral	Quite comfortable	Very comfortable

ID Number: User-____

Approach – Condition 1

How comfortable did you feel when the robot approached to you?

Not comfortable at all	Not comfortable	Neutral	Quite comfortable	Very comfortable

Approach – Condition 2

How comfortable did you feel when the robot approached to you?

Not comfortable at all	Not comfortable	Neutral	Quite comfortable	Very comfortable

Behaviour 1

Behaviour 1 – Condition 1

How acceptable in this situation did you find the robot's behaviour?

Not acceptable at all	Not acceptable	Neutral	Quite acceptable	Very acceptable

Behaviour 1 – Condition 2

How acceptable in this situation did you find the robot's behaviour?

Not acceptable at all	Not acceptable	Neutral	Quite acceptable	Very acceptable

ID Number: User-____

Behaviour 2

Behaviour 2 – Condition 1

How acceptable in this situation did you find the robot's behaviour?

Not acceptable at all	Not acceptable	Neutral	Quite acceptable	Very acceptable

Behaviour 2 – Condition 2

How acceptable in this situation did you find the robot's behaviour?

Not acceptable at all	Not acceptable	Neutral	Quite acceptable	Very acceptable

Behaviour 3

Behaviour 3 – Condition 1

How acceptable in this situation did you find the robot's behaviour?

Not acceptable at all	Not acceptable	Neutral	Quite acceptable	Very acceptable

Behaviour 3 – Condition 2

How acceptable in this situation did you find the robot's behaviour?

Not acceptable at all	Not acceptable	Neutral	Quite acceptable	Very acceptable

ID Number: User-____

Personal Interview Questions

- Life Style:

- What is your favourite activity at home? And what is your favourite outdoor activity?

- What do you like to do in your spare time? How do you spend your days off at home?

- Would you prefer reading a book or listening to music at home? How many hours do you spend watching television per day?

- Do you prefer to stay alone or with other person or friends at home?

- How often do you meet people or your friends at home?

- Do you like to cook by yourself or with someone's help? Do you use book recipes when cooking?

- Personality

- Would you like to travel around the world or just to places close to your country? Would you like to carry out any big adventure, e.g. cycling around your entire country?

- If you like travelling, would you prefer a relaxing (e.g. beach and sunbathing) or an adventure holidays (e.g. climbing or hiking)?

- Do you like to stay on your own rather than staying with people when travelling?

- What kind of sport do you practise? Do your prefer individual or team sports?

- Do you usually have a healthy life style? If not, why do you think so?

- How many hours do you sleep at night on average? Would you say that you sleep well at night?

- Are you the type of person with lots of friends or just a few close ones?

- Robot Interaction:

- Do you like the idea of using robots at home? What are your motivations for using them?

- What would you dislike about using robots at home?

- What are the most important things to you when using robot companions?

- How a robot companion could really help you at home?

- Would you consider a robot as your friend now or in the future?

- Technology and Background:

- How important is technology on your life? Do you use social media?

- How many technological devices do you use on your daily life?

- How easy or difficult is for you to get used to new technologies?

- What do you like about technologies? What do you hate about technologies?

- Imagine a day without using any kind of technology, what would you do?

C.6 Experiment 3 - Consent Form and Questionnaire

ID Number: User___

Introduction and evaluation of the Personas concept in the field of Human-Robot Interaction. How robot companions can be adapted to users' needs and preferences based on the use of this technique

Section 1: Information about the research and the experiment

In the future, robot companions could support us during our activities of daily life at home. In order to make this possible, they have to be aware of the environment and the user's needs in different circumstances, so they provide us with a personalised assistant. Our aim is to investigate and develop mechanisms that allow users enjoy from a pleasant interaction when first encountering a robot. We try to avoid the collection of large dataset which will make easier our tasks defining distinct robot behaviours, but in the other hand, we will put a burden in our users, and probably, frustrate their first experience with a robot companion.

The incorporation of social skills into robots' responses so as to achieve smoother interaction with humans remains a significant challenge. In our previous work, we have tried to understand how people interact with robots, and which theirs preferences are in a domestic environment. This allows us to develop robots which exhibit a greater awareness of context when interacting with humans. The findings from previous experiences have helped us to define the next experiment in which we will reassess our work, and our approach to achieve a smooth and adapted human-robot interaction at home. The UH Robot House is the naturalistic environment used by our research group to perform all these varieties of HRI experiments.

In this new experiment, you will perform a set of scenarios where you will be required to interact with our robot companion, called Sunflower. We are trying to find out which your preferences and needs are when interacting with a robot at home. You will be just required to behave as you would act in your own house and without any kind of pressure, as you are not going to be evaluated. Two sessions, will be required to complete the experiment. The first session begins with a brief introduction about the robot and the house in order to familiarise yourself with the facilities. Next, you will perform three scenarios with the robot, and answer a few questions at the end of each scenario. The first session will require around 1 hour, and the second session does not involve any interaction with the robot; you will just answer a few questions and fill in a questionnaire which will not take longer than 25 minutes.

This research will involve the collection of video material required for the post-experiment analysis. All data gathered on individual participants will be treated with full confidentiality. At no time throughout the whole course of the research project your name or any other personal details provided by you will be identifiable, i.e. your name will not appear in any internal or external publications. An ID code will form the basis of our evaluations, not your real name.

Participation in this study is entirely voluntary. If at any point you do not wish to continue with the study, you may withdraw, this will not reflect badly on you. The questionnaires provided do not have any right or wrong answers, nor should they be viewed as tests. However, you can decide not to answer certain questions in the questionnaires if you do not wish to.

This study was approved by the UH EC2 Ethics Committee under protocol number a1213-13(2)

ID Number: User___

Section 2: Consent to take part in the trials

Name of Main Researchers: Prof. Kerstin Dautenhahn, Dr. Kheng Lee Koay and Ismael Duque

I CONFIRM THAT I HAVE READ AND FULLY UNDERSTOOD THE INFORMATION PROVIDED FOR THE ABOVE STUDY. I UNDERSTAND THAT MY PARTICIPATION IS VOLUNTARY AND THAT I AM FREE TO WITHDRAW AT ANY TIME, WITHOUT GIVING ANY REASON. I AGREE TO TAKE PART IN THE ABOVE STUDY. ☐

WE WOULD LIKE TO USE SOME OF THE VIDEO FOOTAGE OR AUDIO RECORDED FOR FUTURE CONFERENCES AND PUBLICATIONS. I CONSENT TO MY VIDEO FOOTAGE OR AUDIO RECORDED DURING THE EXPERIMENTS TO BE USED FOR THIS PURPOSE. ☐

Name of participant: ____

Signature: ____

Date: ____

If you have any questions regarding the above study, please contact the experimenter:

Ismael Duque – ismaelduquegarcia@gmail.com

Thank you.

ID Number: User___

Experiment Questionnaire

1. **How would you rate the robot's expressiveness during this scenario? (i.e. they way in which the robot tries to catch your attention and communicates with you)**

   Low ☐ High ☐ Not Sure ☐

2. **How acceptable did you find the robot's expressiveness according to your preferences when interacting with a robot companion?**

Not acceptable at all	Not acceptable	Neutral	Quite acceptable	Very acceptable

3. **How would you rate the robot's proactiveness during this scenario? (i.e. the robot makes decisions by itself)**

   Low ☐ High ☐ Not Sure ☐

4. **How acceptable did you find the robot's proactiveness according to your preferences when interacting with a robot companion?**

Not acceptable at all	Not acceptable	Neutral	Quite acceptable	Very acceptable

5. **How would you rate the robot's assistance during this scenario? (i.e. the robot offers its help to transport an object to a different place in the house)**

   Low ☐ High ☐ Not Sure ☐

6. **How acceptable did you find the robot's assistance according to your preferences when interacting with a robot companion?**

Not acceptable at all	Not acceptable	Neutral	Quite acceptable	Very acceptable

7. How would you define the distance between you and the robot during this interaction?

Quite Close — A Bit Close — Exact — A Bit Far — Quite Far

8. How comfortable did you feel interacting with the robot during this scenario?

Not comfortable at all — Not comfortable — Neutral — Quite comfortable — Very comfortable

9. Would you change anything about the way the robot behaved during the scenario that just performed?

Yes ☐ No ☐

Please specify: ____

____

____

Experiment Questionnaire

10. **How would you rate the robot's expressiveness during this scenario? (i.e. they way in which the robot tries to catch your attention and communicates with you)**

Low ☐ High ☐ Not Sure ☐

11. **How acceptable did you find the robot's expressiveness according to your preferences when interacting with a robot companion?**

Not acceptable at all	Not acceptable	Neutral	Quite acceptable	Very acceptable

12. **How would you rate the robot's proactiveness during this scenario? (i.e. the robot makes decisions by itself)**

Low ☐ High ☐ Not Sure ☐

13. **How acceptable did you find the robot's proactiveness according to your preferences when interacting with a robot companion?**

Not acceptable at all	Not acceptable	Neutral	Quite acceptable	Very acceptable

14. **How would you rate the robot's assistance during this scenario? (i.e. the robot offers its help to transport an object to a different place in the house)**

Low ☐ High ☐ Not Sure ☐

15. **How acceptable did you find the robot's assistance according to your preferences when interacting with a robot companion?**

Not acceptable at all	Not acceptable	Neutral	Quite acceptable	Very acceptable

ID Number: User___

16. How would you define the distance between you and the robot during this interaction?

Quite Close	A Bit Close	Exact	A Bit Far	Quite Far

17. How comfortable did you feel interacting with the robot during this scenario?

Not comfortable at all	Not comfortable	Neutral	Quite comfortable	Very comfortable

18. Would you change anything about the way the robot behaved during the scenario that just performed?

Yes ☐ No ☐

Please specify: ____

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Experiment Questionnaire

19. **How would you rate the robot's expressiveness during this scenario? (i.e. they way in which the robot tries to catch your attention and communicates with you)**

Low ☐ High ☐ Not Sure ☐

20. **How acceptable did you find the robot's expressiveness according to your preferences when interacting with a robot companion?**

Not acceptable at all	Not acceptable	Neutral	Quite acceptable	Very acceptable

21. **How would you rate the robot's proactiveness during this scenario? (i.e. the robot makes decisions by itself)**

Low ☐ High ☐ Not Sure ☐

22. **How acceptable did you find the robot's proactiveness according to your preferences when interacting with a robot companion?**

Not acceptable at all	Not acceptable	Neutral	Quite acceptable	Very acceptable

23. **How would you rate the robot's assistance during this scenario? (i.e. the robot offers its help to transport an object to a different place in the house)**

Low ☐ High ☐ Not Sure ☐

24. **How acceptable did you find the robot's assistance according to your preferences when interacting with a robot companion?**

Not acceptable at all	Not acceptable	Neutral	Quite acceptable	Very acceptable

25. How would you define the distance between you and the robot during this interaction?

Quite Close	A Bit Close	Exact	A Bit Far	Quite Far

26. How comfortable did you feel interacting with the robot during this scenario?

Not comfortable at all	Not comfortable	Neutral	Quite comfortable	Very comfortable

27. Would you change anything about the way the robot behaved during the scenario that just performed?

Yes ☐ No ☐

Please specify: ____

____

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ID Number: User___

Post-Experiment Questionnaire

1. **You have performed three times the same scenario but the robot's behaviour has been slightly modified on each situation. Did you appreciate any kind of variation in the robot´s behaviour?**

Yes ☐ No ☐

Comments: ____

____

____

2. **Which of these scenarios could be defined as the most suitable for you? Please, give a reason.**

Scenario 1 ☐ Scenario 2 ☐ Scenario 3 ☐

Reasons: ____

____

3. **How the robot's interface is adjusted to your preferences and needs?**

Not adjusted at all	Not adjusted	Neutral	Quite adjusted	Very adjusted

4. **Would have you changed or modified the interface font size or style at any point during the interaction? All suggestion will be considered in future experiments.**

Yes ☐ No ☐

Please specify: ____

____

5. **Would you switch off the robot's voice and leave just the interface to communicate any action?**

Yes ☐ No ☐

Comments: ____

6. Did you enjoy the experience of interacting with the robot companion in a home environment?

Yes ☐ No ☐

Please specify: ____

____

7. Could you rate your expectations before the experiment regarding the interaction with the robot and how it could help you at home?

Low ☐ Medium ☐ High ☐

Have these expectations been fulfilled at any time by the scenarios performed?

Yes ☐ No ☐

Please specify: ____

____

8. Did you miss any other robot's behaviour or characteristic during the experiment that you just performed?

Yes ☐ No ☐

Please specify: ____

____

9. Based on all the scenarios that you just performed. Could you create your ideal robot´s behaviour choosing between the following robot´s characteristics? :

<u>Expressiveness</u>

Low ☐ High ☐

<u>Assistance</u>

Low ☐ High ☐

<u>Proactiveness</u>

Low ☐ High ☐

<u>Distance Approach</u>

Personal ☐ Social ☐

Comments and suggestions: ____

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Second Session Questionnaire

Personality Questionnaire

The following questions are taken from the TIPI – the Ten Item Personality Inventory. They are intended to measure your personality. It is included because, we are interested in how different types of people view and interact with robots. There are no right or wrong answers to this, and there is not one 'right' personality type for our studies. Also, we will not divulge your responses to these questions to members outside of our research team. Like all data we collect in this study, the personality questionnaire data will be treated anonymously.

Trait	Disagree strongly	Disagree moderately	Disagree a little	Neither agree nor disagree	Agree a little	Agree moderately	Agree strongly
Extraverted, enthusiastic							
Critical, quarrelsome							
Dependable, self-disciplined							
Anxious, easily upset							
Open to new experiences, complex							
Reserved, quiet							
Sympathetic, warm							
Disorganised, careless							
Calm, emotionally stable							
Conventional, uncreative							

ID Number: User___

1. **Do you remember which of the three scenarios you selected as the most suitable for you?**

Scenario 1 ☐ Scenario 2 ☐ Scenario 3 ☐

Reasons: ____

____

2. **Based on the videos showed, could you rate for each scenario how you will describe each of the followings robot´s characteristics?**

	Scenario 1	**Scenario 2**	**Scenario 3**
Expressiveness	Low / High	Low / High	Low / High
Assistance	Low / High	Low / High	Low / High
Proactiveness	Low / High	Low / High	Low / High
Distance Approach	Personal / Social	Personal / Social	Personal / Social

3. **Scenario 1 - Open Questions**

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4. **Scenario 2 - Open Questions**

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5. Scenario 3 - Open Questions

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6. After analyzing the videos, would you select the same scenario as the most suitable for you?

Yes ☐ No ☐ Not Sure ☐

Reasons: ____

____

7. Based on all the scenarios that you just saw. Could you create your ideal robot´s behaviour choosing between the following robot´s characteristics? :

<u>Expressiveness</u>

Low ☐ High ☐

<u>Assistance</u>

Low ☐ High ☐

<u>Proactiveness</u>

Low ☐ High ☐

<u>Distance Approach</u>

Personal ☐ Social ☐

Comments and suggestions: ____

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Appendix D

Ethics Approval Notifications

UNIVERSITY OF HERTFORDSHIRE
FACULTY OF SCIENCE, TECHNOLOGY AND CREATIVE ARTS

M E M O R A N D U M

TO	**Kerstin Dautenhahn**
C/C	**n/a**
FROM	**Dr Simon Trainis – Chair, Faculty Ethics Committee**
DATE	**13 December 2011**

The Ethics approval (Protocol Number 1011/12) for your project entitled:

FP7 European project LIREC

has been granted an extension and this extension has been assigned the Protocol Number:

1112/39

This approval is valid

From 1 January 2012

Until 31 August 2012

If it is possible that the project may continue after the end of this period, you will need to resubmit an application in time to allow the case to be considered.

UNIVERSITY OF HERTFORDSHIRE
SCIENCE AND TECHNOLOGY

M E M O R A N D U M

TO **Ismael Duque Garcia**

CC **Prof Dr Kerstin Dautenhahn**

FROM **Dr Simon Trainis, Science and Technology ECDA Chairman**

DATE **05/02/14**

Protocol number: a1213-13

Title of study: Investigating users' needs and preferences when interacting with robot companion in a domestic environment. How the concept of Personas could be integrated into early stages of HRI studies.

Your application to Amend the protocol detailed above – formerly titled, *Introduction and evaluation of the Personas concept in the field of Human-Robot Interaction (HRI). How robot companions can be adapted to users' needs and preferences based on the use of this technique.*, has been accepted and approved by the ECDA for your school.

This approval is valid:

From: 05/02/14

To: 27/02/15

Please note:

Any conditions relating to the original protocol approval remain and must be complied with.

Approval applies specifically to the research study/methodology and timings as detailed in your Form EC1. Should you amend any aspect of your research, or wish to apply for an extension to your study, you will need your supervisor's approval and must complete and submit form EC2. In cases where the amendments to the original study are deemed to be substantial, a new Form EC1 may need to be completed prior to the study being undertaken.

UNIVERSITY OF HERTFORDSHIRE
SCIENCE & TECHNOLOGY

ETHICS APPROVAL NOTIFICATION

TO Ismael Duque Garcia

CC Prof. Dr. Kerstin Dautenhahn

FROM Dr Simon Trainis, Science and Technology ECDA Chairman

DATE 01/12/14

Protocol number: **a1213-13(2)**

Title of study: Introduction and evaluation of the Personas concept in the field of Human-Robot Interaction (HRI). How robot companions can be adapted to users' needs and preferences based on the use of this technique.

Your application to extend the existing protocol **a1213-13** as detailed below has been accepted and approved by the ECDA for your school.

Modification: Extension of end date because the number of participants on the current experiment is being increased.

This approval is valid:

From: 01/12/14

To: 31/10/15

Please note:

Any conditions relating to the original protocol approval remain and must be complied with.

Approval applies specifically to the research study/methodology and timings as detailed in your Form EC1 or as detailed in the EC2 request. Should you amend any further aspect of your research, or wish to apply for an extension to your study, you will need your supervisor's approval and must complete and submit a further EC2 request. In cases where the amendments to the original study are deemed to be substantial, a new Form EC1 may need to be completed prior to the study being undertaken.

Should adverse circumstances arise during this study such as physical reaction/harm, mental/emotional harm, intrusion of privacy or breach of confidentiality this must be reported to the approving Committee immediately. Failure to report adverse circumstance/s would be considered misconduct.

Ensure you quote the UH protocol number and the name of the approving Committee on all paperwork, including recruitment advertisements/online requests, for this study.

Students must include this Approval Notification with their submission.