Quantifying Human-Robot Interaction by Developing a Measure for Safe Collaboration

Investigating Human Movement and Collaboration in Physically Assistive Human-Robot Interactions

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A thesis submitted in partial fulfilment of the requirements of the University of the West of England, Bristol for the degree of DOCTOR OF PHILOSOPHY *in Safe Human-Robot Interaction Design.*

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Abstract

This research investigated whether human motion prediction by an assistive robot can always lead to a safe and efficient human-robot interaction. Using human motion, prediction can encourage interaction in close physical proximity and can help build trust in collaborative human-robot interactions. However, when the interaction gets more complicated due to external disturbances and the complex nature of the humans, it may lead to physical harm or interaction failures. Despite the literature raising safety issues in physically assistive robots, research regarding potential disturbances and adverse outcomes is limited. Therefore, this research considers the impact of external disturbances and their effect on collaboration.

To address this gap, the present study investigates the consequences of external disturbances on the collaborative state of humans, particularly in the context of assistive tasks in natural living environments like care homes. A comprehensive examination of the impact of disturbances on human motion is conducted through surveys, human-robot interaction experiments, human motion recordings, and observational studies involving professionals in care homes. Two case studies are conducted to analyze different interaction scenarios and complexities, resulting in the collection of two time-series datasets capturing human movement. The first case study focuses on human reaching movement in a shared workspace, utilizing movement primitives to predict and distinguish minor variations in the final reaching position. The second case study examines human movement during an assistive dressing task, introducing cognitive overloading and distractions to evaluate the effects of disturbances in a more complex interaction environment. Quantitative and qualitative techniques are employed to identify differences in movement patterns during these irregularities, revealing that collaboration is hindered in the presence of disturbances.

The findings from the observations carried out in care homes contribute to further analysis of complex interaction and their requirements to provide safe physical assistance. The natural occurrence of successful, safe and efficient collaborative interactions witnessed in care homes, regardless of the vulnerability level of older adults, is examined and questioned. This leads to the belief that a measure of collaboration between humans and robots through input modalities is necessary for ensuring safety. This measure acts as an implicit constraint for the robot, particularly when there is variation between

human and robot movement, especially during changes in the collaborative state of humans. It enables a more realistic evaluation of human motion prediction by directly assessing the safety of continuing collaborative movements.

The aforementioned case studies served as a foundation for further analysis of human movement as input modalities. To ensure physical safety, knowledge similar to that obtained from the second case study can be utilized as priors, represented in the form of latent spaces, to provide information about the human's collaborative state. This approach allows for a more accurate assessment of the safety of continuing collaborative movements. The core contribution of the thesis lies in leveraging the input modality of human movement as an affordance that ensures physical safety in assistive robots, incorporating knowledge about collaboration while considering the influence of environmental factors, human factors, and the human state.

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Author's Declaration

I declare that the work in this dissertation was carried out in accordance with the requirements of the University's Regulations and Code of Practice for Research Degree Programmes and that it has not been submitted for any other academic award. Except where indicated by specific references in the text, the work is the candidate's own work. Work done in collaboration with, or with the assistance of, others, is indicated as such. Any views expressed in the dissertation are those of the author.

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Chapter 1

Introduction

> **The Challenger exploded in 1986:** *"The chart implicitly defined the extent of the relevance, and no one seems to have asked for additional data, the ones they could not see. That is why the managers made the tragic decision to go ahead despite the weather"* by Diane Vaughn as part of her account of the tragedy "The Challenger Launch Decision".
> In this work, we ask professional caregivers to guide us towards the unseen in physically assistive robots. We question the viability and safety of physically assistive robots in different task complexities. The answers lead to defining and understanding the relevance of a safety measure that assesses collaboration in close-proximity physical assistive tasks.

The lesson from the Challenger tragedy is that even though one might have large datasets in the world, sometimes we need better and new data collection. Looking for answers with an incomplete perspective of the problem leads to imposing the wrong questions. Such assumptions can deceive us into looking for solutions from incorrect data. The overarching argument running through this thesis is that is that previous literature insufficiently addresses the delivery of safe assistive \gls{hri} by failing to adequately question the practical needs of end-users and the contexts in which these systems operate. These aspects need to play a more prominent role than we think; otherwise, we are also imposing the wrong questions in assistive HRI. Either we start understanding how our technology can directly address these needs in a realistic environment or start thinking about how we can make these natural environments more welcoming to future technology.

The understanding process that should shape assistive robots research questions must be approached with a safe and ethical point of view towards the older adults' (end-users') needs and, most importantly, empathy. We cannot expect and assume to solve all shortages of carers in care homes with an assistive tool because sometimes it can be undignifying. Furthermore, we need to understand the complexities of humans over time, the challenges that are part and parcel of the interaction environment and tasks, and the limitations of robots, tools and interaction methodologies. Ultimately, this thesis uncovers the need to ask all the *what-ifs* before providing solutions to assistive robots because we cannot afford a 'challenger tragedy' in assistive robots. This thesis questions how the Human-Robot Interaction (HRI) in assistive robots have been theorised within laboratory environments and suggests that a better understanding is needed to directly fulfil the contributions that such research is trying to provide.

Figure 1.1 illustrates the nested arguments of this thesis together with a set of *what-ifs* questions that try to understand the different interaction complexities in realistic environments. The assistive HRI experiments in a laboratory environment are insufficient to claim that the robot's interaction will always be safe and viable, especially when the complexities of the human behaviour are not considered. When unexpected events happen during a complex assistive task, it is essential to consider consequences and question the safety methodologies used in less complex interaction setting to guarantee the same measure of safety. It is also crucial to understand how professional caregivers provide their daily assistance and how they can always guarantee that the older adult's safety is prioritised in an ethically and dignifying way. Consequently, in this thesis, we delve into the constraints of current adaptive robot behaviours, focusing on human movement prediction. It analyses how this approach can ensure safety only within specific levels of complexities in assistive HRI.

> **definition:** ***Unexpected Events (UnEv)*** The occurrence of any form of distraction from the surrounding environment or from the user itself can hinder the planned

interaction between the human and the robot.

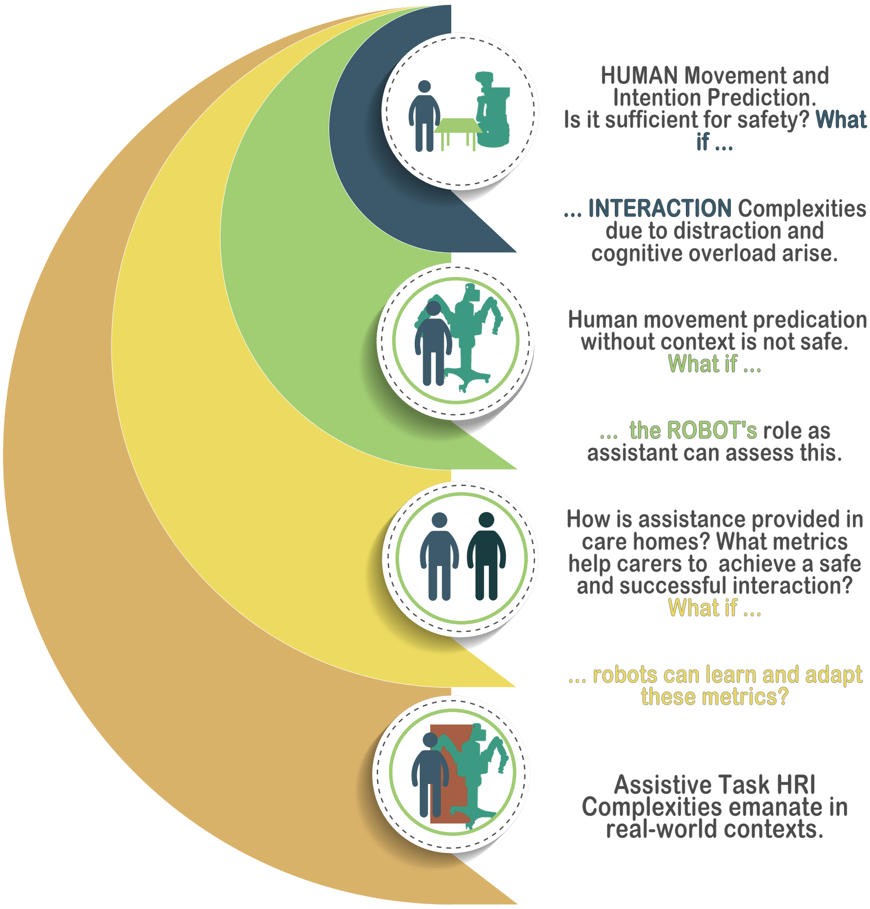


Figure 1.1: A top-down hierarchical view of the main arguments discussed in Thesis.

> **definition:** ***Close-Proximity Collaborative Interaction (CPCI)***
> An interaction that requires a robot to move very close to the human or vice versa. The interaction workspace is directly around the end user and, in some cases, the user itself. The actions of the robot and human are simultaneous, not sequential.
> *Physically Assistive Tasks require close-proximity collaborative interactions before a physically assistive task can take place.*

1.1 Motivation

The development of systems that involve complex robotic interactions is still minuscule when compared to progress in digital technology and machine learning. This is because

HRI is highly dependent on the task and the dynamic environment in which the interaction occurs. These complexities leave a significant gap in research: a completely safe robotic system when interacting in the same environment and sharing the task with humans [66, 131, 151]. The objective for collaborative robots is to achieve a safe commercialization of systems that can recognize, work with, and adapt to human or other robot behaviours in a dynamic environment [7].

To achieve full deployability, it is critical to guarantee a decision-making approach valid for all situations and contexts. This decision-making process must safely adapt to changes in a highly dynamic environment. The decision process must be explainable and safe for other human-operated systems and all humans interacting in the same space. A significant challenge in this research field is related to having a robotic system performing actions or tasks that can be physically harmful in the context of the unpredictable human behaviour. Uncertainty and ambiguity in a decision making process make it harder for such robotic systems to be deployed in an interactive environment with humans. For example, collaborative robots for tasks requiring simultaneous sharing of space, must consider all these hazards to carry out their tasks safely. Such robots are needed in industrial, medical or home environments either in the form of small mobile platforms and/or manipulators. The overall approach to considering HRI in these areas is an interconnection between the autonomous control of the robotic systems and the human inferred intention and behaviour. The complexity of the task and the type of collaboration deepen the intricacy of this interconnection. Ultimately, representing these intricacies in an explainable way leads to providing a good decision process in a highly dynamic environment.

> **definition:** ***Human State (HS)***
> This term in HRI refers to a general term that describes the current cognitive and emotional state of the human during the interaction. See glossary HS. *Other terms used to describe the human state in literature are: acceptance, fatigue, stress, frustration, trust, safety, mental, exhaustion, anxiety, arousal, cognition, workload, sleep, psychological, user state, awareness [72].*

For safety in these interaction contexts, collaborative robots need to be able to classify the actions of human and evaluate the relevance of these actions to the task and the robot's next move. This relevance needs to be continuously verified in the context of the collaborative tasks by being able to anticipate the next move within that action. The validity of the nature of the robot's next move and the human makes it safe for the robotic system to adapt to the user's next movement. For example, in an interactive robot in an industrial or assistive environment, the action classification would highly depend on the task and the number of humans interacting. Action classification for assistive robots can be what type of task the user wants, the human's state and the current state of interaction. The relevance of these actions requires further evaluation predicting the human intention and behaviour within the classified action. Suppose interactions occur in a highly dynamic environment, in that case, many factors can suddenly change the intention and behaviour of the person interacting with the robot.; Therefore, the assumptions on which the robot is adapting its behaviour can suddenly become unfounded.

In physically assistive tasks, the prediction of human intention and behaviour can be the prediction of the individual arm movement and the robot's ability to adapt to it. In these contexts, the prediction needs to be based on some prior observation and knowledge and determine whether the user/human next move is relevant to the current state of adaptation. Most importantly, accurate prediction and relevance of the collaborative task are key determinants of safety. The critical aspects of any close-proximity collaborative interaction with humans can be described as follows [104].

- *Human Movement Understanding*: deals with knowledge of human movement and trajectories in dynamic environments with an added complexity of social and physical interaction between other humans and the robot. Interpreting human motion goes beyond the ability to understand muscle or neural activation and requires knowledge from other research fields, such as cognitive science. Previous research has focused on how humans handle obstacles. However, there is no precise model describing the human ability to process the sensing of the dynamic environment and their reactions due to a changing environment during a collaborative task [104]

- *Motion Optimization and Control*: The robot motion planning and manipulation can be learned from demonstration by representing human motion principles in a utility functions that best describes this imitation. Near-optimal solutions represent these learned behaviours and can be represented in low-feature spaces, scaling down from high-dimensional spaces, which depend on the number of sensor inputs considered for the interaction. However, these representations need to be continuous in terms of the state and action. Therefore, motion optimisation comes into play where motion planning and control require adaptation to obtain better solutions. A better solution is required when the state and action pairing changes due to changes in reactivity and synchronisation [18] explained in *Human-Robot Collaboration (HRC)*.

- *Human-Robot Collaboration (HRC)*: aims at understanding and matching the reactivity and synchronisation of the *Human Movement (HM)* between humans and a robotic manipulator in the environment. Such capabilities require a predictive model of human behaviour integrated with high-dimensional sensing. This aspect of collaborative robots is fundamental in recognising and implementing what humans expect and react to from robot motion in close proximity. These intricacies in the interaction must be characterised and represented by frameworks that evaluate the interaction in a human-in-the-loop way. Such human-aware approaches require predictive models of human behaviour that can be deemed safe in all contexts and situations. To achieving this safety in all contexts and situations is challenging. In practice this requires an HRI framework that optimizes motion based on models of human behaviour with some constraints/ boundaries that represent the interaction safety when changing between state and action pairs.

This thesis provides the groundwork that connects the formal methods of human movement prediction with robot learning to achieve a measure of synchronisation between human and robot movement in a collaborative task. It first examines human movement in a simple interactive task. The interactive task is a board game played between a human and a robot manipulator. Secondly, a case study of close proximity assistive robotics is implemented to evaluate the impact of a dynamic environment on collaborative interaction. For this case study, an assistive dressing scenario is used, where a human is assisted with putting on a jacket by two articulated seven-degree of freedom compliant robot arms mounted on a static platform. This case study, investigates the problems involved in building human movement models when a changing collaborative behaviour is present. Such investigation helps to understand how to enable a safe assistance by consider the collaborative state of the human as one of the state-action pairs. Ultimately, it questions how this state-action pair can be incorporated in the prior knowledge used by the robot to adapt its behaviour. The importance of understanding the change in collaborative behaviour is based on feedback from professional caregivers in care homes.

This work aims to create a safety measure in collaborative tasks by designing a prior that determines the cooperative behaviour of the human with respect to the robot. Such prior will enable us to verify that the robot is adapting its behaviour on the correct assumption that the human is still willing to collaborate and, therefore, safe in the current context. In Section 1.2, the key research questions and objectives are listed. This is followed by a brief overview of the thesis outline in Section 1.3 and in Section 1.4 the main contributions and associated publications are listed.

1.2 Research Questions and Objectives

This research was part of the MSCA-ITN project Social Cognitive Robot Agents in The European Society (SOCRATES), grant agreement no. 721619, which studies different aspects of interaction quality between assistive robots and older adults. One aspect that would allow such robots to become a commercial reality is assuring safety both for the users and the robot. As part of SOCRATES, a set of target applications were put together for each work package. The two applications for the work package of *Interaction Safety Design* were:

- **Modelling and adapting to varying user behaviour:** *"Linda has surfed another fall, and she needs help on a daily basis to dress up and put her shoes on. Some days, the dressing is more difficult due to more intensive Parkinson's tremors, and her dressing robots need to adapt its behaviour to safely put Linda's robe on."*
- **Creating Situational awareness to allow the robot to perform the right action:** *"Katherine is often visited by her children and grandchildren. They like to see how the robot helps her with dressing but often create noise and commotion in the room. Katherine finds it more difficult to interact with the robot due to the background noise and movement. The robot, however, can distinguish interactions directed to him and disregard unrelated inputs. "*

The thesis's primary focus is to evaluate collaboration through movement in close-proximity interactions to identify the instances mentioned in the above target applications. Synchronisation of human and robot movement can be achieved through precise timing and tight collaboration. Identifying what can hinder this synchronisation and representing these situations leads to a step closer to safer close-proximity interaction and, therefore, better interaction quality. On this premise, the following questions are raised:

RQ1: In a socially assistive robot interaction context, is human movement prediction enough to guarantee physical safety?

This research question investigates to what extent human movement prediction can provide information about the collaboration intent of the human and keep physical safety. In the context of a socially assistive robot, variation in human movement are hand related and therefore a reaching action is to be predicted as per these sub-research questions:

RQ1a: What is the most appropriate methodology to predict human reaching movements such that variations within the same reaching goal can be represented and still distinguished between different reaching goals?

RQ1b: Can the human reaching movement be represented in the form of prior knowledge?

RQ1c: Can the human reaching movement prior knowledge be generalised over different humans?

RQ2: In a socially assistive robot interaction context, does the state-action pairing for safe robot manipulation need to change when the collaborative state of the human changes?

To properly address if reaching movement prediction defined in RQ1 can guarantee physical safety in a socially assistive robot, the following two sub-research questions are made:

RQ2a: What is the smallest time window possible that allows a high accuracy prediction of the human reaching movement? Is it small enough to guarantee safety?

RQ2b: Can this human reaching movement prediction guarantee the same degree of physical safety when changing the context from a socially to a physically assistive robot?

RQ3: In a physically assistive robot interaction context, can human behaviour impact their physical safety?

This research question investigates if human behaviour during a physically collaborative task can hinder the synchronisation of human movement with the robot. It looks at the human's collaborative state in a realistic and dynamic environment in which human movement prediction can be not enough. To guarantee safety, in the context of a physically assistive robot is more challenging and therefore these sub-research questions are asked:

RQ3a: Can disturbances in a dynamic environment lead to unusual variations in human movement, and therefore a failed collaboration task?

RQ3b: Can prediction of human movement still guarantee safety during such known disturbances?

RQ3c: In such context, can the state-action pairing remain non-adaptive to guarantee safety during such disturbances?

RQ3d: Can some of the humans become familiar with some of the disturbances in the environment?

RQ3e: Can movement synchronization fail even though the human learned how to adapt and collaborate in the task?

RQ4: Can collaboration intent be gauged from the variations in the human movement and guarantee physically safety from a more complex state-action pairing?

This question investigates if variations in human movement due to disturbance in the environment indicate an intent to the collaboration the human during the physically interaction.

RQ5: What are the requirements for a physically assistive robots to deliver physically assistive tasks?

In order to properly answer this research question the following sub-research questions are posed to carer in care-homes:

RQ5a: How do carers physically assist older people in order to guarantee a physical safety?

RQ5b: What do carers think that the requirements and guidelines for a physically assistive tools or robots should be?

RQ5c: Do carers think physical safety can be guaranteed by only looking at the optimal behaviour of humans?

RQ6: Following from RQ4 and RQ5, how can such prior knowledge be used to couple the human movement and robot's motion planning to guarantee safety in the context of disturbance?

RQ6a: How can the variations in human movement be modelled as a prior knowledge?

RQ6b: Can a measure of collaboration be created from this prior knowledge to indicate a lack of synchronisation and hence a possible failure in the interaction?

RQ7 Ultimately can such collaboration measure be embedded and modelled in the robot's motion planning?

1.3 Research Approach and Thesis Outline

The thesis outline aims to highlight the significance of a measure that captures the collaborative state of the human in physical assistive HRI tasks for ensuring physical safety. The understanding is built upon two case studies that involve real HRI, as well observations conducted in care homes. Two datasets were collected from human participants in two separate experiments, both including recordings of human movement during the interactions. The first Case Study (CS1) focuses on participants' movements while reaching different positions on a shared workspace with a socially assistive robot. The second Case Study (CS2) involves a close proximity robotic dressing assistance experiment designed to incorporate unexpected events. Figure 1.2 provides a graphical representation of the relationship between the chapters and their corresponding studies. A chapters structure is outlined as follows:

- **Chapter 2** defines the methodologies related to the key accepts of human-robot collaboration, human movement understanding and; robot learning and motion planning. The literature review primarily focuses on aspects that are applicable to close-proximity HRI, with a specific emphasis on identifying the types of disturbances that can pose safety risks in such interactions.

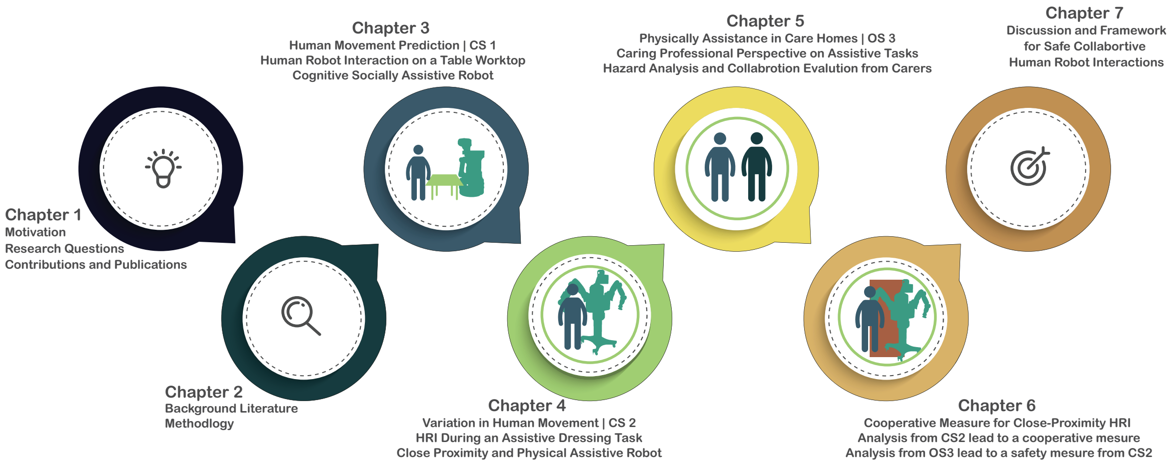


Figure 1.2: Overview of the thesis structure.

- In **Chapter 3**, the research delves into the study of human arm movement by collecting a dataset of recorded reaching positions. Various methodologies are explored to evaluate the accuracy and efficiency in predicting human arm movement final reaching positions. The prediction of the human arm movement is crucial in differentiating between trajectories associated with different reaching positions, thereby identifying distinct movement styles within the shortest possible time frame. The HRI scenario investigated in CS1 involves a socially assistive task with a board on a table as the interaction workspace. The aim is to examine whether achieving a reliable prediction of the reaching area within a small time window can ensure physical safety during the assistive task.

- In **Chapter 4**, a more complex HRI case study is explored, focusing on physically assistive tasks. The workspace for close-proximity human-robot collaboration is the end user itself. Therefore, the prediction of human movement must be robust in all contexts and situations to ensure both safety and efficiency are achieved in real-world environment. CS2 examines a robot-assisted dressing task, considering environmental disturbances and unexpected events. This case study evaluates what leads to variations in human behaviour, attention, and intention during the collaborative task. The experiment is designed to provide insights into how humans learn to collaborate over time and how this collaboration can be easily disrupted when interacting in a natural environment.

- **Chapter 5** examines how caring professionals physically assist older adults. The caring professionals are trained to access the context of the surrounding environment, disturbances or unexpected events. The observation study, referred to as Observation Study (OS3) allows for a deeper understanding of complex HRI by engaging with experts who deliver safe assistance on a daily basis. The hazard safety analysis methods in the literature fail to address the complexity of assistive tasks because they do not consider the necessary *what-ifs* scenarios. Additionally, while the social assistive robot literature emphasizes the importance of moral, trust and ethical measures, physically assistive robots still lack a comprehensive measure for safe assistance.

- **Chapter 6** builds on knowledge gathered from Chapter 4 and Chapter 5 tackling the prediction of failure through the creation of a collaborative measure between the robot and human movements during the collaborative task. This Collaborative measure validated the instance in the second case study in which failure occurred. Furthermore, it connects Chapter 3 and Chapter 6 by coupling the human movement and robot motion in the context of a collaborative task. This coupling leads to a safety measure framework approach derived from the collaboration measure.

- **Chapter 7** recapitulates the work presented in each chapter by providing an overview and discussion on the obtained results presented in the previous three chapters. The main research questions raised are addressed here by highlighting the interrelation of the chapter and the key findings across all chapters. Next, the limitations and future research direction of the work presented are discussed. Lastly, the chapter concludes with a summary of the key contributions.

All the methods and algorithms developed are based on data obtained from the designed experiments. The dataset presented in Chapter 3 was collected on secondment at the Institute of Robotics and Information in Barcelona. The dataset presented in Chapter 4 and Chapter 6 was collected from human experiments carried out at Bristol Robotics Laboratory at the University of West of England.

1.4 Contributions

The primary contribution of this research is the creation of collaborative metric for close-proximity HRI. This work emphasises that relying solely on human movement prediction may not always ensure physical safety. As Collabortive task become more complex, humans are prone to deviating from their optimal behaviour. Figure 1.3 illustrates the

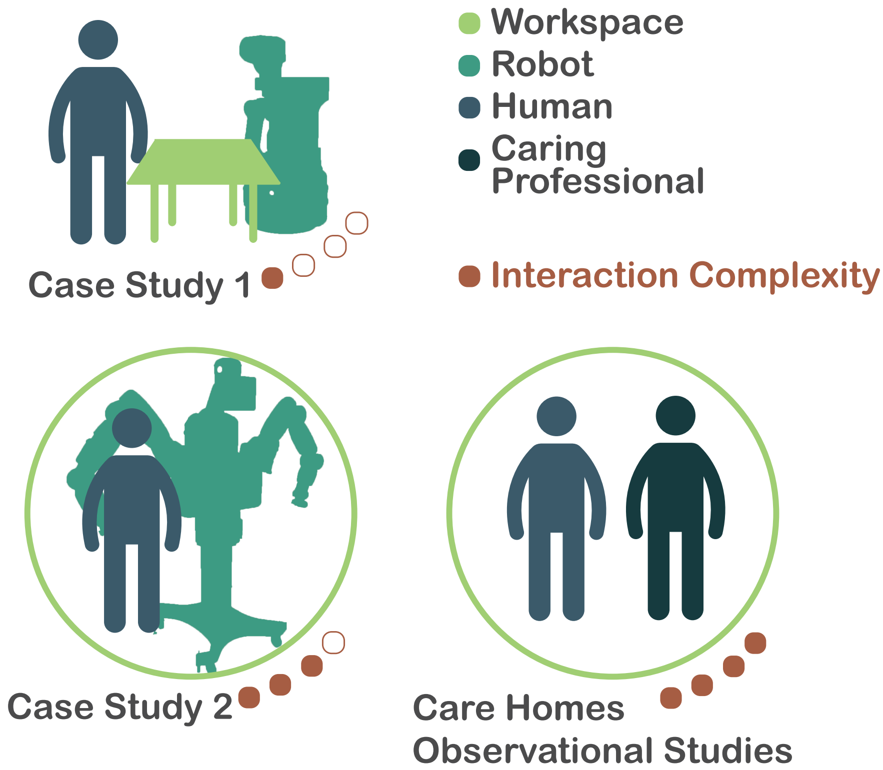


Figure 1.3: An diagram showing the different interaction complexities analysed in all the three case studies. The robots assumed to be used for CS1 is the *TIAGo Robot* by PAL Robotics [116] and for CS2 is *Baxter* by Rethink Robotics [126].

type of studies conducted to assess these deviations in various interaction complexities. The key contributions of this thesis are as follows:

i A dataset of recorded human movement required during interactions with a cognitively assistive robot in a reaching task on a table worktop. Probabilistic Movement Primitives were used for predicting human movement in this case study, and a comparison to other prediction models is conducted - *Chapter 3*.

ii. The second case study CS2 investigates how a dynamic environment can influence human intention and behavior. The dataset in CS2 captures human movement during an assistive dressing task, considering the impact of changes in the dynamic environment on collaborative task performance. The recording of human movements and analysis of overall human behavior shed light on instances where failure in the task may occur, emphasizing the importance of physical safety. This is detailed in Chapter 4.

iii. Observation studies OS3 conducted in care homes explore how carers handle the complexities of assistive tasks in different contexts and scenarios. The studies reveal that proper hazard analysis and collaboration evaluation are crucial factors for ensuring efficient and safe completion of assistive tasks. Chapter 5 provides insights into these observations.

iv. The development of a collaborative measure for close-proximity HRI. This measures utilizes the the dataset from CS2 as prior knowledge and assesses the similarity between the human and robot movement in collaborative and non-collaborative instances. It enables the robots to gauge the level of interaction or distraction experienced by the human partner. Considering that humans may deviate from predicted behavior in the presence of external distractions, evaluating the degree of collaboration becomes essential for synchronization purposes, akin to professional practise in care homes. This measure is discussed in *Chapter 6*

v. Discussion of the previous chapters, leading to the proposal of a new framework that integrates the collaborative measure with appropriate coupling between the robot and the human. The framework emphasize the importance of bounded safety measures on each input modality to ensure safe and efficient close proximity interaction in HRI *Chapter 7*.

1.5 Publications and Scientific Contributions

- **Presented as part of Chapter 3**:
  - Publication - not submitted : A. Camilleri, S. Dogramadzi, and P. Caleb-Solly, **Prediction of Human Movement in the context of Cognitive Assistive Board Games**.
  - Dataset: Human Movement Dataset which consists of 30 Participants performing reaching movement on a table. [To be published].
- **Presented as part of Chapter 4**:
  - Publication [29]: A. Camilleri, S. Dogramadzi, and P. Caleb-Solly, **A Study on the Effects of Cognitive Overloading and Distractions on Human Movement During Robot-Assisted Dressing**, *Frontiers in Robotics and AI* - Human Movement Understanding for Intelligent Robots and Systems, (2022).

- **Presented as part of Chapter 5**:

    - Publication [30] : A. Camilleri, S. Dogramadzi, and P. Caleb-Solly, **Learning from Carers to inform the Design of Safe Physically Assistive Robots - Insights from a Focus Group Study**, in Proceedings of the *2022 ACM/IEEE International Conference on Human-Robot Interaction*, Sapporo, Hokkaido, Japan, 2022, IEEE Press,p. 703-707.
    - A. Camilleri, S. Dogramadzi, and P. Caleb-Solly, Safety Requirements of Physically Assistive Robots - A Study with Professional Carers to Determine Safety Metrics.

- **Presented as part of Chapter 6**:

    - Publication [31]: A. Camilleri, J. Hong, S. Dogramadzi, and P. Caleb-Solly, **Towards establishing a 'Collaboration' Measure for Coupled Movement in Close-Proximity Human-Robot Interaction**, in *Integrating Multidisciplinary Approaches to Advanced Physical Human-Robot Interaction*, ICRA 2020, Virtual Conference, 2020.
    - Publication [not submitted]: A. Camilleri, S. Dogramadzi, and P. Caleb-Solly, "Towards a 'Collaboration' Measure for Coupled Movement in Close-Proximity Human-Robot Interaction

CHAPTER 2

BACKGROUND

The final objective of this thesis is to provide insight and a solution that brings us one step closer to safer Physically Assistive Robots (PARs) by properly evaluating the importance of collaboration in such assistive tasks. This chapter describes the subsection of HRI research in the area of interest of this thesis. Section 2.1, outlines the relevant work for HRI in the context of physically assistive tasks. Subsequently, the section describes the central theme throughout the thesis: collaboration. The first part of section 2.2 describes how robot learning is used to achieve physical safety in physically assistive tasks. Secondly, section 2.2 describes how optimal human movement enables the robots to adapt their learned movement to the predicted human movement for physical safety. Section 2.3 presents an overview of how humans process and behave during collaborative tasks. Finally, section 2.4 describes the safety requirements in care homes for assistive tasks compared to the state-of-the-art and research direction of PARs.

2.1 Approach, Strategies and Methodologies to Human-Robot Interaction for Assistive Tasks

The research area of assistive Human-Robot Interaction (aHRI) is vast, but ultimately it aims to deliver social, cognitive, or physical assistance [107] for tasks without human intervention. The Director-Feneral of the World Health Organization (WHO), in a report from 2018 [59], describes the need for assistive technology and estimates that more than one billion people would welfare from such technology. The WHO states that: *"assistive technology can enable older people to continue to live at home and can delay or prevent the need of long-term care"*. However, providing access to assistive technology to one billion people still comes with challenges in research and development, standards and regulation, manufacturing, supply, services provision, and health emergencies. Overcoming these challenges will ultimately reduce the strain on carers and health budgets [59]. Assistive technology, including robots is constantly undergoing new efforts and developments by employing advances in machine learning and sensing technology [107]. aHRI is a type of collaborative Human-Robot Interaction (cHRI) with a different focus, as the human requires the task rather than the task being assigned to both the human and the robot. Even though the focus is different, aHRI can still involve the aspect of collaboration (see section 2.1.2.1). For these reasons, the new efforts and development in aHRI also benefit from the tenfold growth seen in the cHRI sector between 2015 and 2020 [4] .

Research in cHRI has accumulated interest in recent years, especially due to the formalisation of Industry 4.0 (I4.0) and Industry 5.0 (I5.0) frameworks. I4.0 is technology-driven, whereas I5.0 is value-driven. Technological advancements and solutions are desired only if they align with imperative societal values, needs, and responsibilities [164]. Ensuring that these economic and societal expectations are guarded is arduous, and many challenges are yet to be overcome for a successful deployment. The works of Panagour et al. [117] and Neumann et al. [111] respectively expose how research in I4.0 and I5.0 largely neglected Human Factors (HFs) in the design of HRI. Additionally, limited papers have been identified that considered humans in the cHRI research [111]. So far, in research, HFs are considered dependent variables that the robot factors can manipulate. Only a limited number of research has examined the direct effect that HFs can have on performance and fluency metrics in HRI [72]. If the approach to aHRI is not a joint optimisation problem, then we can never achieve a combination of technology and value-driven frameworks. A strategy of team cohesion between the human and the robot can only be achieved if research starts addressing the gaps by identifying HRI metrics that can be used to address the HFs based on the current HSs [111, 117]. In the literature overview by Hopko et al. [72], the influence by environmental factors (such as context, task characteristics and workspace) and robot factors (such as reliability and automation) are deemed as important as HF and HS. Regardless of this emerged importance, it was reported that no studies were found to include the changing environmental factors (see section 2.1.2.1) and robot factors as direct attributes to the state of the cHRI [72, 99, 125]. These works all highlight that aHRI cannot be based on approaches that are keeping cHRI from being fully deployable [18, 63, 72, 111, 142]. Consequently, based on these gaps in the literature, the thesis focuses on and exposes how to start addressing physical safety through by properly considering the relevant HFs and HSs based on any adaptable environmental factors.

2.1.1 Methodologies in Physically Assistive Human-Robot Interaction

All methodologies in aHRI research aim to assist socially, cognitively, or physically while minimizing the uncertainty caused by unpredictable robot behaviour, human behaviour and other factors. By reducing uncertainty, the reliability and safety of the interaction are improved. This thesis focuses on the third category, which includes physically assistive, industrial and collaborative robotics. Physically assistive robots are a relatively new field of robotics compared to industrial robotics. The methodologies implemented in industrial robotics are mostly control-related, whereas machine learning approaches have only recently been introduced to provide adaptability and complex decision-making in cHRI. Mukherjee et al. [108] argue that there is still a gap in the literature when it comes to combining cHRI with aHRI.

For effective collaboration, the robot must be aware of the surroundings and the human in order to learn how to assist. This is achieved by relying on predictive methodologies based on data gathered from the same surroundings and humans. Such data helps to inform the robot about the HS, HF and environmental factors that aid in improving the robot factors in relation to the assistive task. In physically assistive tasks, this data is referred to as input modalities and is highly dependent on the target users. A large and growing body of literature has investigated various input modalities, including touch input [24, 129, 158], voice-base input [24, 121, 128, 129], eye-based gestures [93, 129, 144], head-movement input [144], facial emotions input, hand or arm gestures and movement [129], brain-computer interfaces [125], bio-metric inputs [125] and physical touch

[8, 99, 129].

However, in PARs and care-home environments, the types of impairments experienced by older adults dictate and limit the use of different input modalities for each assistive task. This perspective is supported by research suggesting that selecting and designing multimodal inputs aligns with providing appropriate support and fostering collaboration for older adults with physical upper-body impairment [96]. In the same vein, research shows that cognitive decline in older adults can restrict communication to non-verbal modalities [85]. While Mingzhe Li et al. [96] focus on how to input modalities assist in addressing human needs, Caleb-Solly et al. in [24] demonstrate that humans have the ability to adapt to the robot's modalities. Collectively this research emphasizes the critical point of selecting input modalities while considering the mutual awareness between that humans and robots. Overall, this literature underscores the necessity for more longitudinal studies to understand how each input modality can be investigated with more robust metrics to deem aHRI physically safe.

The learning strategies used for the robot metrics in physically assistive tasks encompass supervised, unsupervised, reinforcement, and inverse reinforcement learning. While supervised and unsupervised learning focus on specific patterns and structures in the data, reinforcement learning takes a different approach by optimizing a policy to maximize cumulative rewards. However, there is a drawback to using reinforcement learning in this context. The main challenge with reinforcement learning is that in order for policies to converge and encompass all the intricacies of human factors, safety considerations, and environmental factors, a large dataset is needed. Simulating such a dataset is practically impossible, and it becomes apparent that the safety aspects and considerations required in physically assistive tasks are much more complex than what a simulation environment can guarantee. This implies that relying solely on reinforcement learning approaches may not be sufficient to address the full range of factors and ensure the safety of physically assistive tasks. A more comprehensive and context-aware approach is needed to integrate the complexities of human-robot interaction, human behaviour, and the physical environment. By considering these factors in conjunction with learning strategies, this thesis aims to develop a way of how such complex interaction can be analysed and provide knowledge for physically assistive robotics.

Some researchers have demonstrated that the robot metrics used for trajectory planning in close proximity can have an impact on HF and HS in cHRI [18]. These impacts not only affect HS but also have implications for physical safety. Mukherjee et al. also address the issue of physical safety and discuss methodologies aimed at addressing these factors in the interaction [108]. Their work further verifies that, for ensuring physical safety, human factors are just as crucial as robot factors. The highlighted issues in the literature include human errors, physiological safety, human trust, emulation of human emotional states, bidirectional trust, human adaptability towards robots, human action recognition, human action prediction, and human intention prediction. These factors play a significant role in the interaction between humans and robots, and their estimation is crucial for ensuring safety. In the following sections, we will thoroughly evaluate how these safety requirements change in different interaction complexities and how the estimation of HS becomes increasingly important in these complex scenarios.

Ultimately, our objective is to assess how examining complex assistive tasks in real-world contexts can help bridge the existing research gap that hinders the full deployability of physically aHRI . By addressing these safety requirements and considering the complexities of real-world interactions, we can strive towards the successful deployment of physically aHRI systems that prioritize human safety and well-being.

2.1.2 Levels of Complexities in Physically Assistive Human-Robot Interaction.

2.1.2.1 Collaboration, Cooperation and Coexistence

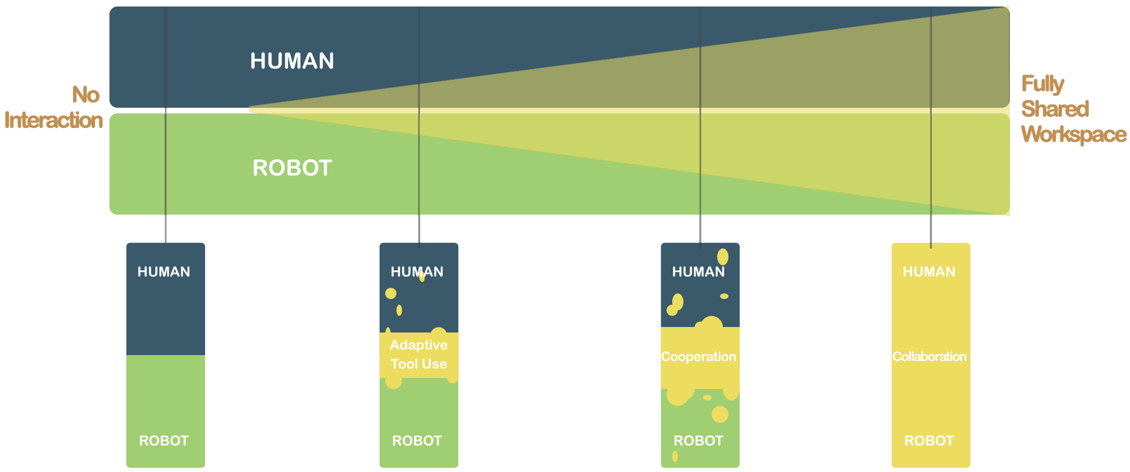


Figure 2.1: Visualisation of the distribution of task responsibilities for different levels of collaboration. This image is adapted from [88] and [89] to fit with the main visualisation, showing collaboration as uniting the effort of the human and the robot.

In order to further characterise the difference between an aHRI and cHRI, researchers define the human roles in the HRI and workspace, time and task sharing as criteria for the classification of complexities in interactions [105]. Others name the levels of collaboration as cooperation and coexistence and would require understanding the basic requirements for the robot to define the level of perception and decision-making [2]. Additionally, any social, physical and cognitive assistance can be remote or proximate (Proximate Human-Robot Interaction)[60]. These characterisations make the different levels of collaboration in aHRI and are extensively tackled in previous literature [2, 88, 89, 105, 148] to try and identify appropriate methodologies for each level. To correctly highlight the gap in the literature we are trying to answer, it is crucial to understand the different types of assistive tasks and contexts that come with different levels of interaction complexities.

Researchers in [88] visualise these collaboration levels to express the increasing collaboration responsibility depending on the task. Therefore an assistive Proximate Human-Robot Interaction (pxHRI) can be collaborative or non-collaborative depending on the characterisations of the HRI task. The authors, Wang et al. [154], also classify these characteristics based on the workspace, nature of the contact, nature of the task and sharing resources. The researchers in [108], after reviewing [2, 88, 105, 154], create their taxonomy that combines all these slight differences and describes the robot's autonomy level. These works suggest that the distance of interaction between the robot and human directly correlates to the interaction complexity. Figure 2.1 shows the adapted visualisation from [89] presented by [88], which indicates that an increasing autonomy of the assistance is to be accompanied by an increasing adaptivity towards the human. Therefore, close proximity physical assistive interaction requires actions that are time-dependent between the respective actions of the robot and human to fulfil the interaction goal. What stands out in Figure 2.1 is the variability in complexity levels which must be accompanied by variability in methodology to guarantee interaction quality and safety at the different levels. Based on these levels of collaboration, this thesis investigates case studies in different levels of complexity. The ultimate aim is to study the requirements and how this can change to maintain safety when moving along these levels to highly complex physically aHRI tasks, where the workspace and task are highly dependent on the human in the interaction.

In Figure 2.2, our case studies are projected on the *Interaction Task Space* to show their respective complexity level. This *Interaction Task Space* shows the HRI characteristics based on the interaction's nature. The vertical axis represents the timing of actions, sequential or simultaneous processing. The horizontal axis represents the intersection of the robot's workspace with the human's workspace; the far left is a separate workspace, and the far right is a shared workspace. The intersection of these parameters portrays the various applications and tasks in HRI as described in [88]. The four corners of the *Interaction Task Space* represent different complexities in HRI as cooperating, coexisting or collaborating to perform a task. The level of complexity in the collaboration of these corners is also visualized in the distributions shown in Figure 2.1. The OS3

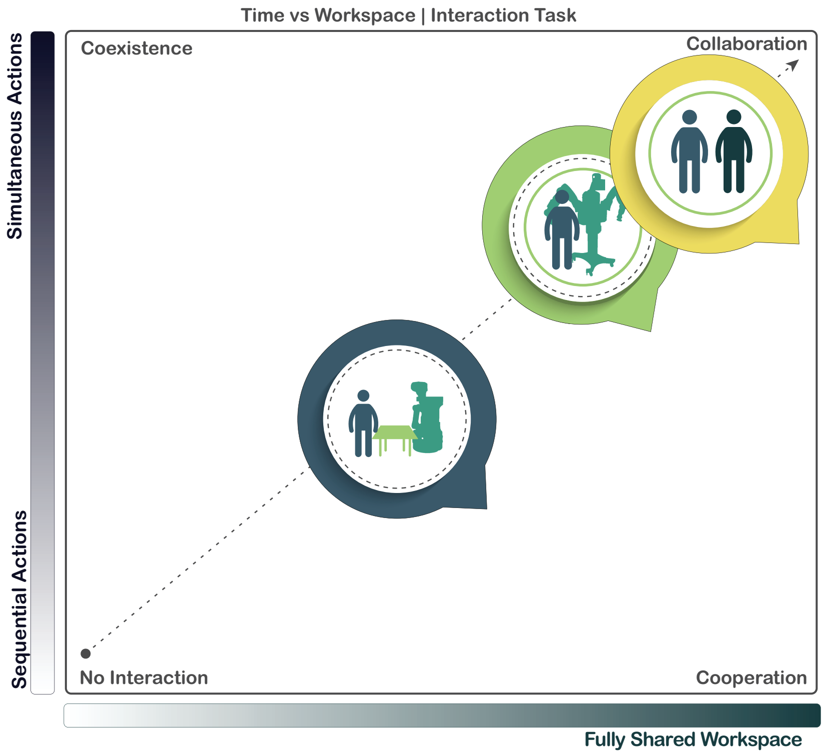


Figure 2.2: HRI complexity characterisation plot showing the level of complexity in each case study. Each corner of the Interaction Task Space is one of the distribution task responsibilities in Figure 2.1.

(yellow marker), assistance by professional carers to older adults, is the most complex type of interaction and should be used as a benchmark for any assistive HRI. The CS2 (green marker) is the physically robot-assisted task of dressing, one of the tasks carers perform daily, and therefore a similar level of complexity to OS3. CS1 (blue marker) is the socially assistive cognitive game in which actions are primarily sequential, and the workspace is a tabletop. The complexity of interaction is highest at the top right corner of the *Interaction Task Space* because all interaction actions shift from sequential to simultaneous in an ultimately shared workspace. This top right corner in Figure 2.2 is the last distribution of task responsibility in Figure 2.1. This thesis aims to ask realistic *what-ifs* for this top right corner by looking at an actual interaction from OS3 and address the gap in the literature of interaction scenarios like CS2.

The above characteristics interchangeably have a significant impact on the **human** and **robot** while both being susceptible to the **surrounding environment**. During an interaction, these three main components influence each other and, therefore, directly or indirectly affect the *interaction quality*. Not considering the complexity of the human, the robot and the environment can lead to failure in achieving the goal or task. The implication of the following interaction parameters relies on carefully selecting the approach and methodology used to solve a particular interaction problem. To better understand the level of complexity in our case studies, we can apply the taxonomy presented in [108]. The set T contains the entire set of tasks, subtasks and actions possible in an HRI-enabled environment for these taxonomies. Elements from this set are associated with human actions $\{T_h\}$ and robot actions $\{T_r\}$. The binary indicator functions $E(k)$ and $E(u)$ represent a set of known and unknown environmental conditions, respectively, and $E(.)$ is used to represent any level of interaction at any instance. Finally, the universal function is $D = F(.)E(.)$, where $F(.)$ is the output decision pertaining to the set of input parameters $\{T_h\}$ and $\{T_r\}$ in the presence of the current environment conditions $E(.)$.

CS1: $\{T_h\} \ominus \{T_r\} = \{T\}$ **and** $D = F(R)E(k) + F(H)E(.)$

In the cognitively assistive robot case study, cooperation exists between humans and robots. Cooperation is another level above coexistence since both agents possess autonomy but share space and resources to achieve the common goal. Their respective roles are decoupled, and their actions occur in a sequential manner. Decisions are taken separately, and even though there are instances when the actions of the human affect the robot's next decisions, the sequential nature of the task space allows the symmetric difference between the two task spaces to provide the entire set of tasks. There is no physical contact here, and the robot operates at an adapted speed.

CS2: $\{T_r\} \cap \{T_h\} \neq \emptyset$ **and** $D = F(R,H)E(.)$.

In the physically assistive robot case study, a form of collaboration occurs between the human and the robot since continuous autonomy is needed from both agents to share a workspace and carry out simultaneous actions as tasks to achieve the final goal. The decisions are made based on parameters from the human and robot that fit the common task elements at any level of interaction for any instance of the environment (known and unknown) conditions. The intersection of $\{T_h\}$ with $\{T_r\}$ can also vary depending on the task itself, but overall for a collaborative interaction is the above taxonomy.

OS3: $\{T_{r_{carer}}\} \cap \{T_h\} \neq \emptyset$ **and** $D = F(R_{carer}, H)E(.)$

The observation study of professional carers $\{T_{r_{carer}}\}$ is an ideal collaboration example for any robot since the carers interact for any overlap of the task with the older adults $\{T_h\}$. The main difference from CS2 is their ability to carry out tasks for $E(.)$ (any given level of interaction at any given instance) and always guarantee safety. The collaborative level here can also be maintained where the intersection of $\{T_h\}$ with $\{T_{r_{carer}}\}$ changes depending on the individual needs of the older adult. In this context, the taxonomy of collaboration still applies but for any $E(.)$ and all possible intersection combinations of $\{T_{r_{carer}}\} \cap \{T\} \neq \emptyset$. Such contexts make more complex responsibilities in the level of collaboration. Hence, the universal function D can only be achieved due to the carers' capabilities as the interaction agent.

From these taxonomies, we can see what is dependent on to make the collaboration successful while guaranteeing physical safety. In particular, when there is an intersection between $\{T_h\}$ and $\{T_r\}$, a shared representation is necessary. In a philosophical review by Bratman [21], collaboration is stated to involve the agent's need for an internal model that allows them to anticipate the future states $E(.)$ of themselves $F(R)$, the other agent $F(H)$ and the task T. Additionally, forms of communication can help explain these models to the other agent and make collaboration successful. In such a way, you would be able to direct someone's attention to the focus on desired for the task[139]. Literature of cognitive science states that joint attention T can provide the basis for a common perceptual ground [139] and that it is a crucial mechanism for successful joint actions leading to fewer errors and reduced task complexity in less time [110]. Shared representations or notions of internal models and the ability to communicate or at least direct the attention of the human within a joint reference framework are undoubtedly critical features for collaboration behaviour. Furthermore, as shown in figures 2.1 and 2.2, the degree to which such representations exist and are shared represents a crucial criterion for distinguishing between levels of collaboration.

In OS3, the ability of the carer to have a shared representation is what makes their assistive tasks successful daily. Comparing these different case studies (different levels of collaboration) allows us to target this shared representation from a different perspective and look at when there is no common perceptual ground for the interaction. In other words, we want to learn how carers approach such tasks when there is no joint attention in a physically assistive HRI and assess how we can apply this to robot-assistive tasks. In aHRI, complexity increases depending on the humans' physical ability and their sensory and cognitive health. The human ability or state can have a considerable effect on interaction safety. Having a human distracted or not paying attention due to fatigue or cognitive overload adds more complexity to the interaction. The environment also plays a vital role in the overall interaction. Any repercussions or changes in the environment can affect the HRI, and for safety, this needs to be carefully considered. During such instances, no shared representation of the joint task T can exist since the joint attention is disrupted.

In Chapter 1, we stated that, for the level of complexity of close-proximity, collaborative interactions consist of *Human Movement Understanding*, *Motion Optimization and Control*, and *Human-Robot Collaboration*. *Human Movement Understanding* is necessary for both CS1 and CS2; however, in the shared workspace of the physically assistive task, the knowledge about the shared representation and joint attention is critical to the safety of the human in question. Therefore the human movement understanding methodologies in literature might not address the gap in the literature when there is no joint attention. Consequently, the assumption on which human movement is understood is no longer valid since the shared representation of the collaborative task is also not valid. The human movement prediction methodologies understood to work in CS1 might not be adequate for CS2. When it comes to *Motion Optimization and Control*, the interaction of $\{T_h\}$ and $\{T_r\}$ is what dictates how successful the collaboration will be as long as the learned behaviours of the robots are valid for $E(.)$. Therefore, if only near-optimal behaviours are learned when there is no joint attention, the shared representation of motion optimization is also not valid. Finally, *Human-Robot Collaboration* is directly affected by the task, workspace and interaction nature. It is used to understand the reactivity and synchronization of the human movement between humans and a robotic manipulator in any given instance in any environment. However, as stated by [21, 110, 139], the task will not be successful if there is no common perceptual ground on which the collaboration is based. The collaborative interaction is disrupted if any changes in the context and situation occur. In these instances, safety cannot be maintained as the shared representation and assumptions of the environment, and humans are not valid. Therefore, in this chapter, we exposed the gaps in the literature on these three aspects concerning lack of joint attention and an inaccurate common representation of the task. CS2 is experimentally designed to create instances where the collaborative intention is disrupted, and a lack of common perceptual ground is made. Ultimately we want to address this gap in the literature by understanding how such context and situation can be learned in models for motion optimization based on the realistic understanding of human movement in a collaborative task.

2.1.3 Research Gap and Thesis Contribution

Consequently, based on these gaps in the literature, the thesis focuses on and exposes how to start addressing physical safety through one metric of HRI by properly considering the relevant HFs and HSs based on any adaptable environmental factors. The contributions towards this gap in research are made in the context of aHRI through the evaluation of human movement predictions as a metric. Ultimately, the taxonomy of CS2 and OS3 will be analysed to find ways how to ensure that there exists joint attention in order to keep the aHRI physically safe. The OS3 is needed to evaluate what is required when there are unknown environmental factors $E(.)$ at any given level of interaction at any given instance.

2.2 Physical Safety in Assistive Human-Robot Interaction

Physical interaction is typically rarely used in complex robot-assisted applications. The goal of these assisted living applications is only achieved with a limited number of input modalities, and safety is never at the centre of this interaction. As part of a dressing task, where close physical interaction is required, [165] focuses on pulling trousers along the legs. The subject's safety is addressed by recognizing the state of the manipulated clothing and visual and force sensory information. The research team at Georgia Tech created mechanical assistance for people who have difficulty dressing themselves. [166] relies on cloth simulation to extract data which could classify the dressing task into three scenarios: successfully going into the sleeve, missing the sleeve opening completely or getting caught by the gown. They divide the system into three main stages: optimization, simulation and classification. The first stage optimizes the parameters of a physics simulator by matching the simulated data to three haptic data sequences for one participant from the real-word. This results in new simulated haptic data. In the final stage, hidden Markov Models are trained with the simulated data to classify real-world test data accurately. [48] used a physics-based simulation and data-driven methods to find the forces being inferred on the person's body using only end effector measurements(force and position) during an assistive dressing task. The method used is that of a long short-term memory (LSTM), which outputs a force map consisting of hundreds of inferred forces across the person's body. This methodology approach is not applicable in the context of CPCI since force feedback is not available.

The authors in [166] present a new method of learning that can adapt to dynamic model parameters and sudden changes in the environment. On the other hand, [57] believes that having personalized assistance will help in reducing the burden of daily living activity and proposes an approach for home-environment assistive humanoid robots to provide assistance for dressing applications. The clothing garment tested was a sleeveless jacket. Furthermore, the I-Dress project at Bristol Robotics Laboratory at UWE addresses some of the problems associated with dressing in the context of physical HRI by predicting the type of garment that the user is wearing through assessing end-effector's forces in [36] and [35]. All of the above-mentioned research attempts to target physically assistive robots but fail to acknowledge the context of close proximity interaction and always assumes that the human behaviour is non-erratic and goal-directed and performing at an optimal or near-optimal collaboration state. For physical safety, this cannot be hypothesised.

2.2.1 Physical Safety: Robot Learning for Assistive Tasks

The physically assistive robotic task requires complex motion to achieve human-like adaptation during the interaction. These complex motor skills are represented by the known Movement Primitives. The dominant method for representing movement primitives is the DMPs [75, 119, 135].

The DMPs are a combination of a forcing term to represent the movement and a stable non-linear attractor. The attractor in this dynamic system affirms asymptotic stability, and the forcing term enables it to follow a specific movement. The general idea of a DMP is to take a dynamical system with stable properties and add another term by modulating it with another non-linear term such that it achieves the desired trajectory based on the attractor behaviour[76]. An improvement to the formerly present DMP is the PDMP presented by [119]. The probabilistic approach allows obtaining an inference from sensor measurement to measure the likelihood that the movement primitive is being executed correctly. The drawback of this approach is that of generated movement primitives, which deviate from the demonstration since not being a data-driven approach. The difference, when compared to ProMPs, is that ProMPs allow the ability to make inferences from the force so that the robot to pass by several initial via points. Both approaches allow for temporal scaling of the movement, learned from a single demonstration to the new final position. Temporal scaling is a requirement for our application to allow realistic adaption to unexpected alterations in human motion. Other ways of inferring the truth have been obtained by minimising the error between the inferred position from the human brain activity of the next time step and the ground truth obtained from demonstrations.

Additionally, in [100], a probabilistic approach to movement primitives is implemented by using a time-warping method based on the Gaussian basis model to represent a time-warping function. The method allows alignment between the two movements without skipping indexes. This allows for a more realistic and smoother projection of movement primitives. In [119], a review of dynamic movement primitives is presented. DMPs can be approached from various aspects; one of them is by adding prior knowledge with imitation learning or trial and error learning with reinforcement learning. Additionally, DMPs are allowed to perform multiple obstacle avoidance through the approach of reactive control with direct feedback from the environment. Ultimately the [119] propose a Dynamic Bayesian Network to integrate perception and action through the concept of associate skill memories.

These characteristics of DMP can adequately incorporate prediction and adaptation in close-proximity. Further, the ability to be able to restrict and couple the representation in the latent variable movement of the predicted trajectory will allow the coupling of the dynamic movement primitives of the robot trajectory to that of the unexpected human arm movement. The probabilistic approach will be used to infer the predicted human arm motion in time. Additionally, the projection of the DVBF with the DMP will adapt movement entirely by representing various movements in the latent close proximity because the restriction of movement representation with that of the robot is critical for safe coupling. Additionally, having a conjoint, capable methodology for projecting, coupling and restricting both the human's and robot's motion is ideal for achieving a coherent safe and adaptive collaboration that is also time-dependent. The advantage of having time-dependent Variational auto-encoders is that of updating the prior in time and representing the context at hand.

2.2.2 Physical Safety: Human Movement Analysis and Intention Predictions in Assistive Tasks

When humans and robots collaborate, mutual understanding is vital for the success of the shared task. Mutual understanding incorporates that the human is attentive to the robot's current task, state, and goal and additionally to predict what to do next and vice versa. Foreseeing a human's intention implies that the robot should be able to interpret the verbal and non-verbal cues that humans naturally use to identify each other's intentions. A simple approach can be that of the assumption that each action is a goal-directed movement. [138] reported on how humans implicitly attribute their intention using gaze to inform their goals to the robot. In [54], a method called Bayesian Human Motion Intentionality Prediction was implemented to geometrically infer the human motion hitting the target. using the Expectation-Maximization and a simple Bayesian classifier. [155] proposed the Intention-Driven dynamics model, based on GPDM [155], to infer the intention of the opponent during a ping-pong match. The intention was achieved by looking at the entire human movement before the human hits the ball.

A more composite procedure for intention recognition is to estimate the future trajectory from past observations. This involves predicting the forward dynamics of the modelled human motion as a dynamical system. An efficient methodology for predicting a trajectory is based on using motion primitives. This entails the generation of a parametric time model to provide a sequence of points of the trajectory. [75] method of Interaction Primitives uses the dependencies between collaborative human movements to learn a distribution over the dynamic movement primitives (DMP)'s parameters. This is further explored in [16] through observations of two humans collaborating using a motion capture system. Estimating in time, the state of the human is necessary to adopt the robot trajectory at any level of interaction coherently. For example, in [52] the robot infers the human intention utilizing the measure of the human's forces and by using Gaussian Mixture Models. In [133], the arm impedance is adapted by a Gaussian Mixture Model based on measured forces and visual information. Many studies focused on the robot's ability to act only when and how its user wants [33, 143] and to not interfere with the partner's forces [77] or actions [12]. Bayesian networks have also been successfully used in [97] and[37] to track human postures.

In the literature, the use of human movement primitives projection on a latent space as a real-time coupling for robot trajectories in an assisted dressing task has not been found. The challenge in human movement prediction stems from the high-dimensional movement representation, which increases the difficulty of learning and inverse kinematics that can sometimes comprise redundant degrees of freedom representation. The authors in [39] show that variational auto-encoders (VAE) can project more meaningful manifolds in the latent spaces than auto-encoder of the traditional principle component analysis (PCA) . Auto-Encoders can be described as non-linear, unsupervised dimensionality reductions method that tries to represent the input data in a latent space by minimizing differences between the input and the output instead of predicting the output based on the input. Gaussian Process Latetn Variable Models (GP-LVM) [19, 94] and denoising Auto-Encoders [38] have been implemented for movement representation in latent space using DMP. In [39] DVBF and (DMP) are used to learn movements from a multi-dimension. The integration of DMPs with DVBF increases the constraints of the latent space, which therefore forces the prior distribution of the movement to be more meaningful to the respective task. The advantage over ProMP is that when a different task is present, the combination of DVBF with DMP adapts movement entirely by representing various movements in the latent space.

Furthermore, human motion trajectory prediction can refer to either prediction of the next movement in general, for example, pedestrian movements as presented in [146] or the actual joints prediction for producing the human pose as presented in [41]. For safety, both types of predictions are critical in HRI which takes place in a common space of the surrounding environment. However, when it comes to collaboration tasks with robotic manipulators, human pose prediction and monitoring is an essential feedback component that adaption depends on. In cHRI the robot requires to maintain an interactive skill which dynamically adapts to changing goals and obstacles. These abilities in robots can be learned as movement primitives, either dynamical movement primitives (DMPs) [136] or probabilistic movement primitives (ProMPs) [118]. Such primary skills can be learned by demonstrations, optimised or generalised accordingly, as shown in [16, 26, 27, 42, 103]. The importance of correlating movement in CPCI is critical in order to enable the adaption of these learned skills. This coupled adaption is presented by Ben Amor et al. in [16] which shows a way of learning the inherent correlations of a collaboration interaction to infer the behaviour of the partner and to participate in the collaboration by coupling the movement. These so-called abilities and skills of performing manipulation tasks can also be attributed to human movement. A mixture model of human-robot interaction primitives is presented in [101] that allows us to infer human movement from observations. On the other hand, in [42] it is shown that human intention can be inferred during physical collaboration after human demonstrations are used to guide the robot. On the other hand, Mainprince et al. in [102] present an interactive re-planning process to capture the adaption to the human reaching motion in shared work spaces.

2.2.3 Research Gap and Thesis Contribution

From this research, it can be summarized that when it comes to human collaboration tasks [16], the interaction is always executed in the context where the partner is fully aware of collaborating with the robot. The ability in the human skill is assumed to be constant or at least not changing frequently. In any HRI that involves close proximity, particularly if the interaction involves physical assistance, it is critical to have prior knowledge about how human skill varies when not fully vigilant during the interaction. According to our knowledge, the variations of human movement skills to perform a physically assistive task due to any distraction have never been researched and modelled. Being able to know to what extent we can manage to represent these variations through a collaboration measure can help in the adaption of the assistive task. The changes in the movement to execute the task cannot be just represented by general movement, but it requires further in-depth evaluation to describe the collaboration in the task. The advantage of having such a measure is that of having a natural cost function that can describe the viability of the continuous adaption of the robot in terms of the current state. Assuming that the motion prediction is pattern-based, as explained in [134] and affected by the dynamic environment cues, we need to have a measure of how the correlation between the movements of the human and the robot varies when the human is distracted due to external disturbances. We would also like to know how these disturbances affect the learned skill of the human for performing the assistive task. Based on these arguments, we want to create case studies to show if failures CS2 in assistive tasks can happen and what is the best way to deal with them OS3. The aim is to evaluate how robot learning can be adjusted to include the additional knowledge of cognitive overloading or distraction in the surrounding environment. Ultimately we want to evaluate if it is possible to be done implicitly through the input modality of human movement. The contribution of this work is to visualise the variations in the correlation between the movements of the human and the robot in the assistive task when the collaboration and attention are shifted away from the assistive task. Furthermore, we introduce the concept of a collaboration measure by analysing in what ways this natural cost function can be presented most appropriately - in the form of new skills, simple distance measures, trajectory matching or correlation.

2.3 Understanding the Human Behaviour in Collaborative and Assistive Tasks.

2.3.1 Predicting Actions and Interactions: the human perspective

In any research context, both robots and humans need to predict each other in order to achieve collaboration. When humans interact with other humans or complex objects, they seek predictability in their interactions. This implies that humans desire predictability and naturalness in their interactions with robots, especially in the context of physically aHRI.

Human collaboration encompasses various aspects. Firstly, humans tend to converge towards an initial state to simplify subsequent actions within the interaction. Secondly, they strive to minimize transitional periods and reach a steady state more rapidly. Lastly, humans actively work towards increasing predictability and synchronization in their interactions by maintaining a steady state. Results from the literature that studies collaboration between humans show that humans learnt to simplify the interaction forces with other objects, making interaction more predictable.

However, it is crucial to acknowledge that the ability to maintain this steady state is not always within their control. While it is widely recognized that anticipating human motion is crucial for intelligent systems that coexist or interact with humans, there remains a gap in the literature when it comes to addressing situations where the steady state cannot be achieved or sustained. This represents an important area of research that requires further exploration and investigation. To be able to address the complex interaction of CS2 and OS3 this cannot be only analysed through data collection from simulation. If research continues to do so, only near-optimal behaviours are learned and when the steady state cannot be maintained and when there is no joint attention, the shared representation of motion optimization and prediction cannot be valid. Simulations offer a convenient and cost-effective means of collecting data compared to real-world systems. In the context of robot learning, the accuracy and reliability of simulation models play a crucial role in determining the robot's decisions regarding poses and trajectories[55] . However, the simulation does not represent the real-world context that physically aHRI are required in. The taxonomy of CS2 and OS3, it is essential for the robot to possess knowledge about the human's state at any given instance, even in unfamiliar environmental conditions, to ensure physical safety. In situations where elevated mental stress or distraction is detected, a collaborative robot can have the capability to mitigate the risk by adjusting its speed, providing physical support to the human, or modifying its end-effector trajectory. Surprisingly, there is a scarcity of studies that have explored the implementation of tailored assistive robot actions in response to humans' mental stress or safety awareness during collaborative tasks[99].

2.3.2 Human Collaboration, Mental Models and Cognitive Overloading and Distractions

Understanding human cognition and mental model is necessary when instigating a lack of collaboration in interactions. Neuroscience research defines action cognition as the amalgamates of human motor control, perception, and cognition [58] and that it can be mathematically formulated to describe human adaptive behaviour as a resistance to a natural tendency to disorder. One principle that can explain these mathematical formulas is the free-energy principle which states that the human brain actively makes observations while concurrently minimizing the world's model [56]. This equilibrium obtained from the minimized free-energy model will be disrupted when an unexpected event occurs. The human reaction would be to minimize the differences between their free energy world model and the world updates brought by their senses and associated perception. The work presented in [56] suggests that human movement gets disrupted when trying to minimize these differences in the collaborative task. The impact on the equilibrium described in the works of [56, 58, 115] is similar to the disruption of a shared task representation due to a lack of synchronicity described in [40, 140, 141]. Disruptions during task performance, and hence the world model, can be due to *cognitive overloading* and/or environmental *distractions* as defined by [115]. Cognitive load is the amount of information that a person can hold in their working memory at a given time [56, 58, 115]. Memory can be classified into short-term, long-term, working and sensory memory. Sensory memory perceives and preserves auditory and visual cues in short-term memory. On the other hand, working memory takes new information and organizes it among already learned information that is stored in the long-term memory [56, 58, 115]. Long-term memory is effectively limitless, unlike working memory, which is essential for learning and performing a task. When unexpected events occur during a physically assistive task, the working memory has to process new information, increasing the cognitive load. The ability to work with robots together to achieve the task can be greatly impacted in these instances, and understanding the joint interaction can be crucial in interaction contexts similar to CS2.

2.3.3 Intention Estimation and Joint Attention

Literature that analyses intention estimation and joint attention states that a team can be seen as a group of individuals who share a joint intention, which refers to their collective commitment to perform a coordinated action while being in a shared mental state. The establishment of a joint intention requires the team members to understand and estimate each other's intentions and to agree on working together towards a common goal [162]. In the case of a cHRI and aHRI, human needs typically set the goal and may not always intend to achieve it. The robot's role is to estimate this intention and take appropriate actions to assist the human in accomplishing the goal. The intention of a person can be communicated either explicitly through deliberate communication or implicitly through actions. Problems can arise when the mental stress on the working memory disrupts communication or when older adults are not able to communicate. Therefore in this thesis, we want to evaluate the possibility of estimating this through human movement.

Achieving synchronized motion between humans and robots is crucial for the successful completion of collaborative tasks. However, this synchronization can be affected by external factors. Humans possess unique capabilities and limitations that can either enhance or impede the accomplishment of physically collaborative tasks. According to the work of Haddadin et al. [68] the safety of the robot's collaborative mode depends on taking into account the human's collaborative intention during the task. It is important to further investigate potential disruptions in the collaborative state of humans in order to ensure safe and smooth recovery from these disruptions and facilitate adaptive robot behaviour.

Existing literature reviewed in this area assumes that human behaviour either correctly adapts to robot movements or remains consistent throughout interactive tasks. However, our concern is that collaborative human movement can be disrupted, leading to a loss of synchronicity in certain situations. The literature on close-proximity interactions mainly focuses on task completion through continuous adaptation to human movements, without considering the possibility of discontinuity that may arise in different dynamic environments. It is crucial to address these potential disruptions and explore strategies for maintaining synchronization and graceful recovery in order to ensure effective collaboration between humans and robots.

Collaborative HRIs are typically addressed through prediction and adaptation by the robot, whereas the human collaborative state is assumed constant [16, 53, 120, 153]. Prediction in HRI relies on evaluating the current interaction state and choosing correct actions [71, 137]. In [71] a reactive and anticipatory action selection is compared. The anticipatory approach combines the current state with a probabilistic view of the temporal activity, providing better efficiency over the reactive approach [71]. The work presented by [16] involves interaction primitives that combine the probabilistic temporal view of the movement variation with performed adaptation. Both [71] and [16] state that the robot is interacting with an engaged human. Hence, in such works, the selection of the appropriate anticipatory action can only be done with a high level of confidence when there is mutual responsiveness and commitment to the collaborative task. If the human is not in a collaborative state, it can potentially pose a safety risk.

In other related studies, which are focused on physical contact, ([49]), adaptation of the robot movements considers changes in human movement, but changes in human behaviour (distinct to specific movements) due to distractions or cognitive loading are not addressed. In an assistive dressing task, human movement is in close proximity to the robot, and for safety, it requires high confidence in predicting and adapting the robot's movement. Distractions and failure are very likely in a real-life context, and a clear understanding of human engagement and movement changes is required. Robot-assisted dressing failures have been considered by [35], but analysis and modelling of the human's collaborative state in the presence of disruptions were not included. Additionally, the changes to the synchronicity cannot be modelled using a probabilistic approach or be recognized as yet another movement primitive, as shown in [42], if the probabilistic models are not trained on a disrupted human movement dataset as shown in [155]. Similarly, the modelling of human motion uncertainty has only been performed for collaborative tasks. The works of [79, 86, 165, 166] and [57] model this uncertainty in close-proximity collaborative tasks in specific scenarios in which either a global trajectory is learned or motor skills are encoded. However, the human movement modelled in these studies is for general skills to perform a task without considering disrupted human movement. Therefore, if a lack of synchronicity between movements affects the representation of the shared task due to an uncooperative partner ([40, 140, 141]) then these learned motor skills need to encode such information for safe physical Human-Robot Interaction (pHRI). This encoding will allow the recognition of non-collaborative instances during pHRI.

Furthermore, the non-linearity and high dimensionality features comprising human behaviour can be challenging to investigate. For human movement analysis, dimensionality reduction is used to express the limb-based characterization in a more readable space. This methodology takes advantage of visualization to spot disruption within the human movement as a change in collaborative behaviour. Latent variable models ([114]) are used to address these challenges([79, 167]) to model limitations in human movement or to personalize human movements.

2.3.4 Research Gap and Thesis Contributions

Therefore, in conclusion understanding human cognition and mental model is necessary when instigating a lack of collaboration in interactions. Based on these related works, we hypothesize that cognitively overloading humans with the robot-assisted dressing task will disrupt the synchronicity of their collaborative physical interaction. We consider how *cognitive overloading*, as well as *distractions*, will unbalance the overall cognitive load made up of intrinsic, extraneous and germane loads. The aim is to address the lack of addressing of the impact of mental stress and how this affects physical safety. In order to properly evaluate this timing unexpected events will be considered and staged to trigger increased mental effort. CS2 experiment will explore these hypotheses by taking care of the temporal layout of these staged events (see Figure 4.1). The nature of the unexpected staged events is based on how to research describes how to disrupt the equilibrium in the mental model by looking at the different cognitive loads, which are further explained in Section 4.2.2.

We also hypothesise that a change in a human's collaborative state can lead to a change in human movement. This hypothesis is based on work from [58]. In this thesis, we want to be able to visualise this in the input modality of human movement and model the discontinuity of the human's collaborative state through human movement observations. Therefore we aim to create a series of controlled HRI experiments in which we can observe variations, limitations, and differences in human movements in the presence of disruptions during a collaborative task. Again, disruptions included in the experiment were based on relevant literature on human behaviour, action cognition and motor control. The aim is to have data that is not based on simulation and that can provide knowledge about what happened when the joint intention of collaborating is disrupted. In a robot-assisted dressing context, physical interactions start when human limbs are inside the dressing garment. The aim is to contribute to the research gap by showing how when humans are exposed to distractions and cognitive overloading, their collaborative state can change even before the physical interaction starts and impact their movements. Additionally, the aim is to understand whether this lack of joint attention can be identified through data from the input modality of human movement. To further analyse the data of human moment we use a related approach to model the human movement and highlight any disruptions associated with the change in collaborative behaviour. The method used is the Gaussian Process Latent Variable Model (GP-LVM), which is a Bayesian non-parametric model which acts as a dimensionality reduction method by using a Gaussian Process(GP) to learn a low-dimensional representation of high-dimensional data. The advantage of using such a method is using the non-linear learning characteristic of GP, which is ideal for human movement ([167]). The non-parametric model properties allow a distribution-free form model with a flexible structure that can scale to accommodate the complexity of the dataset.

2.4 Carer's Requirement for Physically Assistive Robots

In the introduction chapter, we discussed the necessity of comprehending the process through which physically assistive robots are designed to support older adults, as well as the importance of considering all the *what-ifs* concerning physical safety (see Section1.2). By employing this approach, we examine the aspects of physical safety in assistive robots by considering various interaction complexities. By utilizing human movement as an input modality, we examine the implications for physical safety when transitioning from a socially assistive interaction context (**RQ1** and **RQ2**) to a physically assistive interaction context (**RQ3**). This prompts a critical assessment of the requirements necessary to ensure physical safety, particularly by examining how caregivers perform their assisting tasks (**RQ5**).

The overview provided in this chapter highlights the lack of consideration for these requirements in the current state of the art, especially in terms of incorporating adequate HF and HS during the design process (**RQ2** and **RQ4**). The importance of adopting a holistic approach is also proposed in the WHO framework for people-centered health, accentuating that care itself is a value and originates from the patient's perspective. This encompasses patient safety, patient satisfaction, responsiveness to care, human dignity, physical well-being and psychological well-being [157]. Given the lack of standardized guidelines and early stage of development, it is crucial to integrate care-centered designs for such technology [150]. Achieving this integration requires proper consideration of how to incorporate these aspects of care and interdisciplinary collaboration between robotics engineers, designers, programmers, philosophers, psychologists, and software engineers. Preliminary studies suggest that establishing trust between users and robots fosters a more collaborative attitude and a higher tolerance for increased autonomy, enabling the completion of complex assistive tasks [47]. The summary provided in this chapter regarding the current state of the art indicates that these requirements have not been addressed up to this point. This research provides direct evidence of the significant benefits of HF in designing robots, as a more collaborative attitude leads to successful assistive tasks.

In literature, there is this continuous claim that the interests of carers and older adults are marginalized when it comes to assistive robots. In some instances, the interests of the carer surpass those of the older adult, while in others, the physical safety of the older adult can outweigh the ethical and privacy issues [78]. These different points of view and arguments can only be understood through a proper long-term analysis of the environment in which physically assistive robots are to be used. It is highly important to assess the real-world environmental factors, HF and HS from the perspective of the carers and have them establish the requirements needed to fulfil the criteria of physical safety. Studies have shown that carers express appreciation for the benefits of assistive robots and are open to employing such technology in care homes, but only if a fully functional automated approach can be provided. Carers also believe that such assistive technology can help older adults if it starts to consider what caregivers need and provides assistance to them, especially when it comes to cognitive impairment [15]. Ultimately, the requirements emphasized in the literature indicate a willingness to introduce technology as long as it properly considers the needs of older adults, carers, and any factors that can impact the assistive interaction. Furthermore, the current literature highlights the ***importance of rating all work in physically assistive robots for older adults based on the level of collaboration between humans and robots*** [47]. These claims support the foundational requirements outlined in this thesis. The literature gap we are addressing involves introducing the needs of older adults by examining how carers carry out their own tasks. The research questions the approaches to human movement prediction in different interaction complexities while maintaining a value-centered approach of physical safety. Answering these questions requires a deeper understanding of the factors that can impact physical safety at higher levels of collaboration while considering a more realistic environment and carefully assessing the effect of the HS. According to evidence in the literature of the current state-of-the-art, the answers to the appropriate *what-ifs* can and need to be identified by the carers themselves. With this in mind, the objective of this thesis is to examine the design PAR by considering the perspective of carers in real-world scenarios, specifically focusing on the evaluation of physical safety concerning human movement.

In conclusion, although most of the current literature addresses some of the aforementioned requirements none of them appear to have considered a holistic approach to utilizing an input modality that provides feedback on a value-centred approach of physical safety based on the carers' perspective. This approach, with a focus on the users' needs at the appropriate level of complexity, will ultimately lead to an assistive robot design that aligns with the required collaboration standards [47].

2.5 Summary

This chapter provides an overview of physically assistive robots, specifically focusing on robots designed to assist physically impaired older adults. The primary research topics examined are human movement prediction and robot learning for assistive tasks. It becomes apparent that the design of robot factors is often not adequately considered in relation to HF, HS, and environmental factors. Overall, there is a lack of a holistic consideration of all the factors that affect the behaviour of the human and interactions. The research concluded that collaboration tasks are not considered in an environment where the unknown in the environment can, directly and indirectly, impact the joint attention to collaborating in the assistive task. From the taxonomies that describe the complexities of interactions, it was noted that to maintain physical safety, the methodology used in simpler interaction contexts will not provide this. Therefore, we want to evaluate how much robot factors in physically assistive tasks can be improved to consider these unknowns. All research always assumes the optimal behaviour of the human. This invalidates the taxonomies of the most complex interaction scenarios since you cannot guarantee physical safety if this is not properly considered.

Moreover, research on human mental models, behaviour, intention estimation, and joint interactions reveals joint attention's susceptibility to disruption in collaborative tasks. This highlights the existing gaps in research and emphasizes the need to address these shortcomings to enable successful physically assistive human-robot interactions.

Additionally, it is important to note that no prior work has effectively addressed the requirements of physically assistive human-robot interactions based on the insights and expertise of professional carers in care homes. Their experience and knowledge are invaluable in shaping the development and implementation of such tasks. Therefore, it is crucial to explore how professional carers currently approach these tasks and analyze how their approach can be integrated into the operation of robots performing physically assistive tasks.

In conclusion, this chapter highlights the need for a more comprehensive and inclusive approach to physically assistive robots. It emphasizes the importance of considering the interplay between human and robot factors, addressing the impact of unknown environmental conditions, and incorporating the expertise of professional carers. By addressing these research gaps and improving our understanding of physically assistive human-robot interaction, we can pave the way for safer and more effective collaboration in the field of physically assistive robotics.

CHAPTER 3

Human Movement in a Socially aHRI Task

3.1 Introduction

With the aim to leverage the input modality of human movement as an affordance that ensures physical safety in all interaction complexities, this thesis starts exploring human movement and evaluating the extent to which it can provide physical safety for older adults. The methodology involves assessing real-context human movement to understand the knowledge it can offer in terms of time and space, and if it can guarantee predictability and physical safety in both socially and physically assistive tasks.

In this chapter presents CS1, a case study involving an aHRI tool aiding cognitively training for older adults with dementia using Social Assistive Robotic Agent (SARA) [9, 10]. It focuses on whether human movement prediction within this

In order to evaluate this, a human movement experiment and data collection were designed and implemented. The resulting time-series dataset was then prepared, cleaned and analyzed. Our goal was to explore how human movement data manipulation and visualization could serve as priors for predicting future aHRIs and cHRIs. The results demonstrate the feasibility of human movement prediction and the effectiveness this approach in distinguishing between slightly different movements. The results demonstrate the feasibility and effectiveness of human movement prediction in distinguishing between subtle movements. However, certain constraints and observations, crucial in addressing the lack of physical safety solely through human movement prediction, are further discussed in the subsequent chapter.

3.1.1 Research Questions

In summary, three research questions will be investigated in this chapter through these human movement experiments:

3RQa Can subtle difference between similar human reaching movements for different reaching positions be differentiated from one another through prediction? (see section 1.2, **RQ1a, RQ1b** and **RQ1c**)

3RQb What is the most accurate approach for movement prediction while minimizing the prediction time window? (see section 1.2, **RQ2a**)

The research questions in this chapter are also aligned with the main research questions previously described in section 1.2. Specifically, the primary research questions addressed are **RQ1** and partially **RQ2** (see section 1.2).

3.1.2 Contributions

In answering the above-mentioned research questions, the following contributions are made:

- The dataset was collected from 30 participants whilst performing reaching movements towards a shared workspace with a socially assistive robot.

- Validation of human movement prediction methodology as a means to differentiate between highly similar human reaching movements.

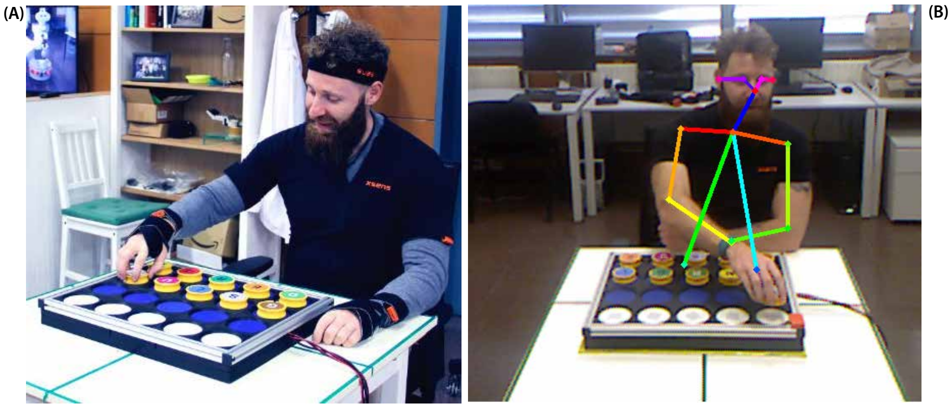


Figure 3.1: Different methodologies to recorded human reaching movement. Sub-figure A shows the Motion Capture Xsens suit and sub-figure B shows the OpenPose and PointCloud merging.

3.2 The Socially aHRI Task and Interaction Context.

3.2.1 Experimental Layout and Data Recordings

The socially aHRI task facilitates assistance to dementia patients through a board game. Figure 3.1 shows the workspace shared between the patients and the robot. The games assesses the cognitive and physical abilities of the patients by encouraging and instructing them to sort numbered tokens on the board (see Figure 3.1). Each one of these tokens is on one cell on a board placed on a table. The older adult and the robot sit on opposite sides of the table. The board is equipped with Radio Frequency Identification (RFID) sensing, allowing the SARA to detect when a token is picked and where it is placed. The exercises can involve:

- Sorting five odd tokens in ascending order.
- Sorting five tokens in ascending order.
- Sorting five numbers in descending order.
- Moving first storage row to goal row.

When lettered tokens are used in the cognitive training, additional exercises can involve:

- Spelling a 5-lettered word.
- Sorting five tokens in lexicographical order.

These exercises are designed to help the cognitive function of the older adults by working with the robot to complete task correctly. The current state of the exercise refers to the position of the token IDs on the electronic board. This position knowledge forms the precondition part of the action. An action is defined by a *precondition* and *effect* where the effect is the possible token adjustment that can modify the current state by changing the token position from one cell to another. The term 'trace' represents to the possibilities that the caregiver can provide to allow the SARA to learn the rules required to place a set of z tokens in five correct positions. These traces will generate at least x preconditions (depending on the type of exercise), some of which can be redundant. Non-technical professionals can modify the SARA by straightforwardly programming the traces. As part of the first interaction loop, a caregiver can implement the configuration of the rules. The second interaction loop describes the interaction between the robot and the older adults through speech and gestures to encourage patients to complete the exercise correctly and in the least possible time.

For the second loop, user-centred interaction design is facilitated through the implementation of the Persona-Behavior Simulator (PBS) which generates a high level of abstraction for the user's action that can be employed in the SARA in cognitive training scenarios. The learning of these abstraction levels is presented in [11]. The benefit of a PBS is that being able to generate data for HRI scenarios more efficiently and feasibly. The PBS provides the ability to learn an assistive policy that can adapt the SARA behaviour by offering more or less assistance towards completing the cognitive exercise based on the current state of the environment and the robot's action.

The main two components of the PBS are the Persona Definition (PD) and the Task Engine (TE). The PD is the static component based on the memory (the patient's cognitive impairment), reactivity (the patient's physical reactivity) and attention span (the patient's ability to keep focus). On the other hand, TE is the dynamic component which shapes the given state through the complexity and number of attempts. The complexity characteristic is the probability of guessing the right move at a given game state. This probability will be different for different patients (personas) at a given environment state.

3.2.2 SOCRATES Secondment Collaboration Contribution

PD is defined as a static component; however, the characteristic described in [11] as safety risk can be dynamic. During the cognitive training, patients interacted in the same workspace, manually picking tokens from the board. The SARA also uses the same workspace, to suggest a possible token as the next move. User errors, unexpected events or any form of distraction during the interaction can divert the older adults' attention from the cognitive exercise on the board. This can result in incorrect token movements or abnormal trajectories of the older adults' arm in the shared workspace above the electronic board. These incorrect moves can pose a physical hazard to the older adult if the cognitively assistive robot cannot predict their intention to move to an unexpected cell on the tabletop board. The complexity characteristic in the TE can be better inferred if the trajectory of the older adult's arm can be predicted based on initial trajectory observations during the interaction. Each cell on the board is associated with a specific token through the RFID technology. Collecting human movement data allows us to identify the intended cell position before the action is executed and, consequently, determine the goal intention by predicting the movement trajectory of the older adult. Therefore the contribution to the SARA is that of providing physical safety through prediction of the human movement. Human movement prediction adds knowledge about the HS based on HF in addition to the state of the environment and robot's action already considers through the dynamic and static components.

These are results obtained during a SOCRATES secondment visit to another Early Stage Researcher (ESR) who developed the SARA. The secondment is a requirement of the SOCRATES project and aims to find a common research goal between ESRs.

3.3 Methods

Figure 3.2 displays the markings on the workspace around which the SARA provided the assistive interaction. The board, on which the tokens are placed, measures approximately 45cm by 36cm. The various markings show the distinction between possible reaching movements. At a higher level, prediction can either predict larger sub-spaces of the board marked in green (A) and red (b) or the actual reaching cells where the tokens are located. The more complex reaching movement included the ability to differentiate between reaching movements for different cells. The TIAGO from PAL Robotics robotic platform is used the assistive robot (agent) in the SARA.

The Xsens suit is used to record the dataset of the human movement reaching (see Figure 3.1). This equipment is a motion capture suit used to capture the joint position and orientation of the human body at different segments. 23 frames are collected from a set of inertial measurement units (IMU) attached to the suit. The focus in the scope of this chapter is on the upper body, particularly the right/left arm. The suit is worn by the

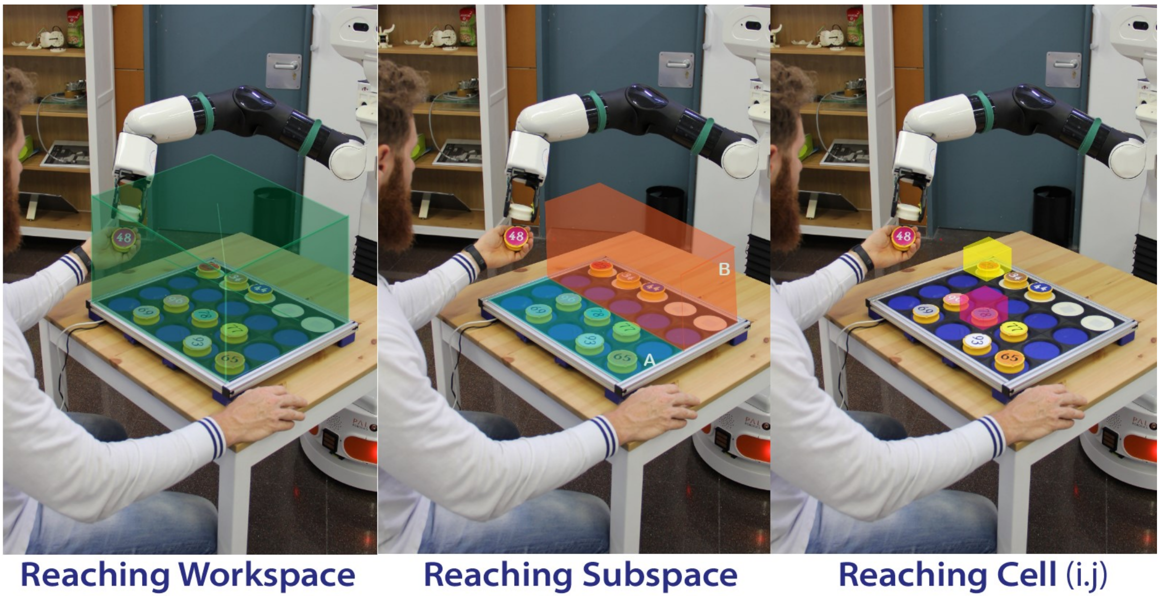


Figure 3.2: The desired objective of human reaching movements in the context of a aHRI around a common workspace. The workspace is a table where a cognitive game is being played, and the reaching subspace refers to the area on the table where the tokens are located in the different cells positions. The goal is to reach each and everyone of these cells, indicated as the final reaching position for the human's movements.

participants in the form of strips attached to arms and legs together with a bodysuit that holds the shoulder IMUs and battery pack. The advantage of using this motion capture suit is that it ensures continuous even when the assistive robot occludes the field of view in the workspace. Moreover, when calibrated correctly, the readings from this suit are more accurate compared to RGBD cameras. However, it is important to note that it is not practical to have patients wear this suit in real life-scenarios, and the calibration process can be time-consuming.

During the secondment, another method was implemented by merging the OpenPose and PointCloud methodology to acquire the 3D position of the joints, as shown in Figure 3.1. However, for the purpose of this study, the focus is assessing the extent to which human movement prediction methodology can provide physical safety in such interaction contexts. Considering the limited duration of the secondment and the need to prioritize accuracy, the decision was made to concentrate solely on movement prediction rather than on extracting accurate 3D joint positions from the 2D OpenPose results.

Figure 3.3 shows the board, the tokens, a user with the XSens Suit and the targeted rows for the cognitive assistive task. The top, middle and bottom rows are highlighted with their respective cell numbers. From figure 3.3, illustrates the visually marked cells

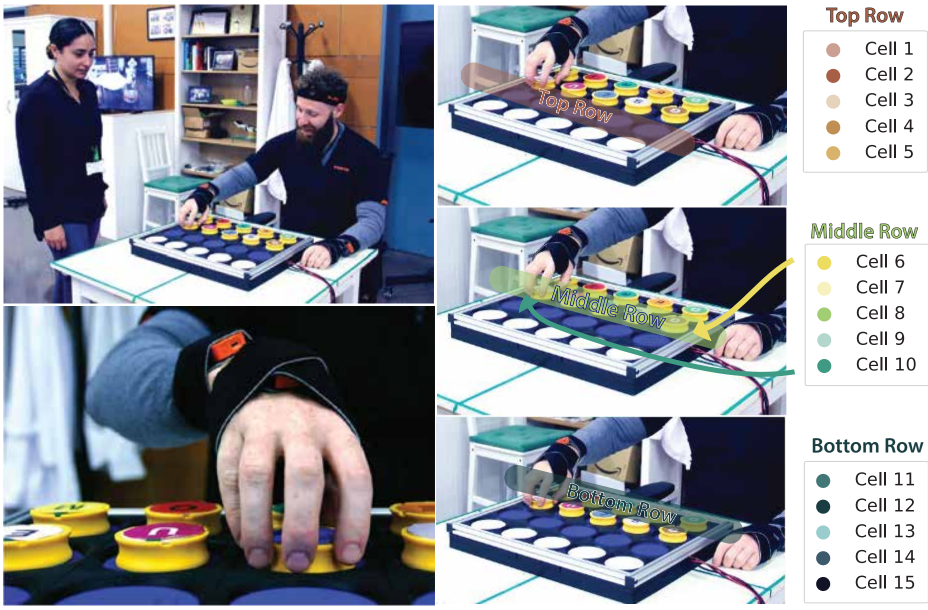


Figure 3.3: Workspace layout where each token or cell position on the board can be a reaching goal for the older adults.

on the board. Participants were instructed to perform reaching movements to retrieve tokens placed at these marked positions. Five cells meaning five tokens could be placed on each row, and therefore for this **CS1** we will consider 15 cells in total. The middle row in Figure 3.3 shows how the far left cell (Cell 6), whereas the far right cell is(Cell 10). This cell labelling format is also kept in the top and bottom rows. It is important to note that colour coding for each cell in the legend of Figure 3.3 is kept consistent throughout this whole chapter.

For the data collection, ethical approval had to be obtained from the board of the IRI institution before proceeding with recording the human movement. The ethical approval document was written in Spanish and can be found in the appendix (see Appendix A). In total of 30 participants took part in the data collection of human reaching movements. However, the data of three participants data was corrupted, possibly due to slightly lower battery levels, and therefore, this was not available for the data analysis. Figure 3.4 illustrates the different skeletons of all the participants, along with their respective joint-to-joint lengths, which would be used in this **CS1**. The joints of interest include the arms, torso and head.

In total the time-series dataset comprises the position*(x,y,z)* and rotation *(x,y,z,w)* of 23 frames. Each frame represents one of the 23 body segments, including joints, the head, or parts of the spine. Prior to data collection, a set of measurements (height, hips height, shoulder width, arm's length etc.) were taken for each participant to calibrate the suit and ensure accurate recording of joint movements. All participants used their right arm to perform the reaching movement.

The data collection process was divided into three main parts with each part starting the participants' arm from a different position. The first position was on the table right next to the board, the second was the chair's armrest, and the third was with the arm resting on the participant's leg. The reason for having three different starting positions was to make the human movement prediction as realistic as possible and assess its performs in such contexts, ensuring that the data can be easily generalised. The experimental setup included a chair and a table, upon which the board was positioned. The distance between the table and the chair remained constant throughout the experiment. Moreover, the board was consistently situated within a marked area on the table delineated by tape.

The reaching movements from these the three starting positions to the 15 cells were repeated ten times, resulting in a total of 450 reaching movements for each participant. Therefore, each participant contribute a time-series dataset consisting of 450 reaching movements. In total, the dataset encompasses approximately 12,150 reaching movements.

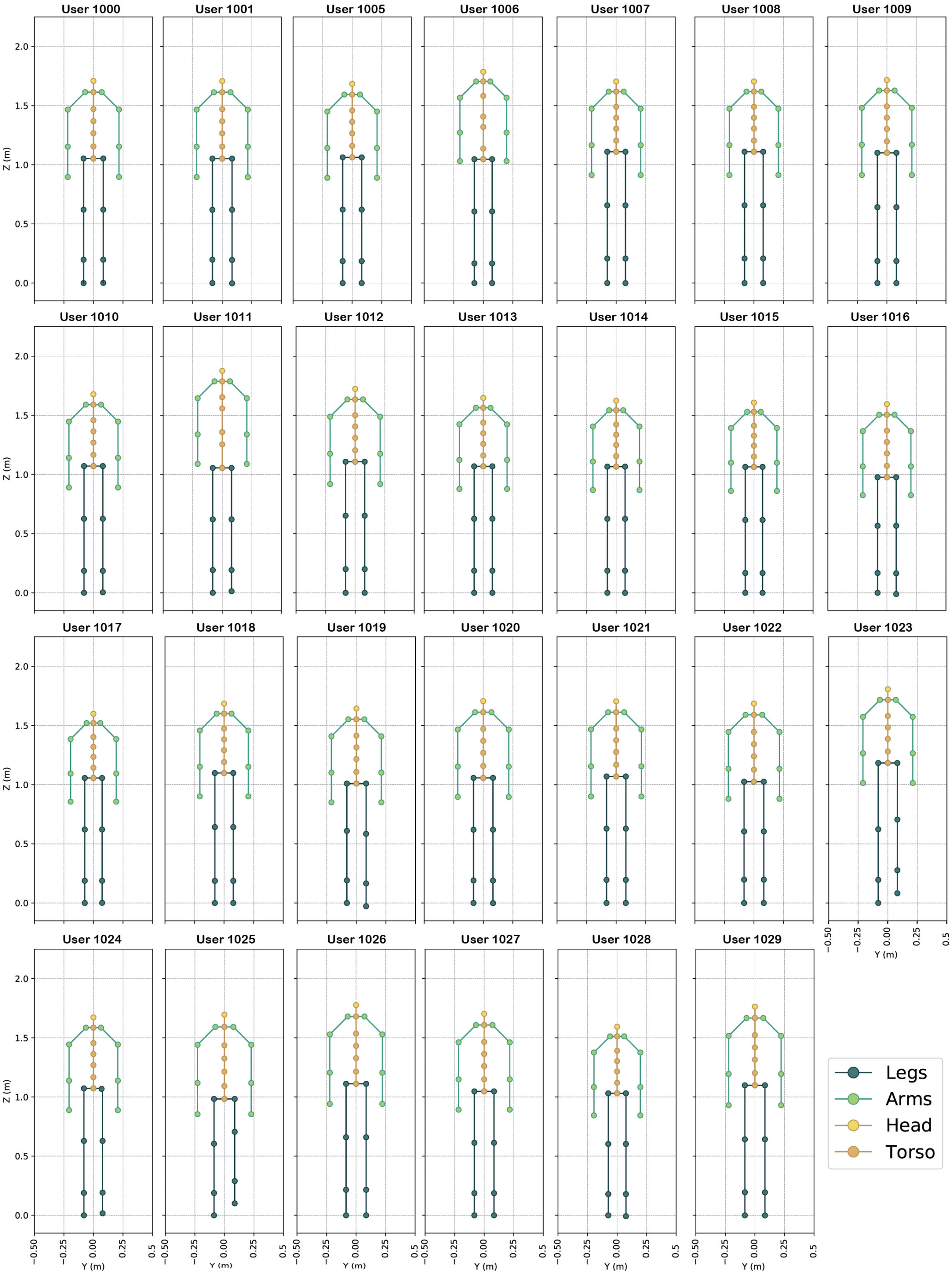


Figure 3.4: The skeleton of participants showing joint-to-joint lengths for each participant. These lengths were necessary for calibration purposes. The legs, arms, head and torso are colored differently. Each sub-figure shows 23 joints of each participant for which the X-Sens suit was used to record the complete dataset as shown in Figure 3.5.

3.3.1 Data Preparation and Cleaning

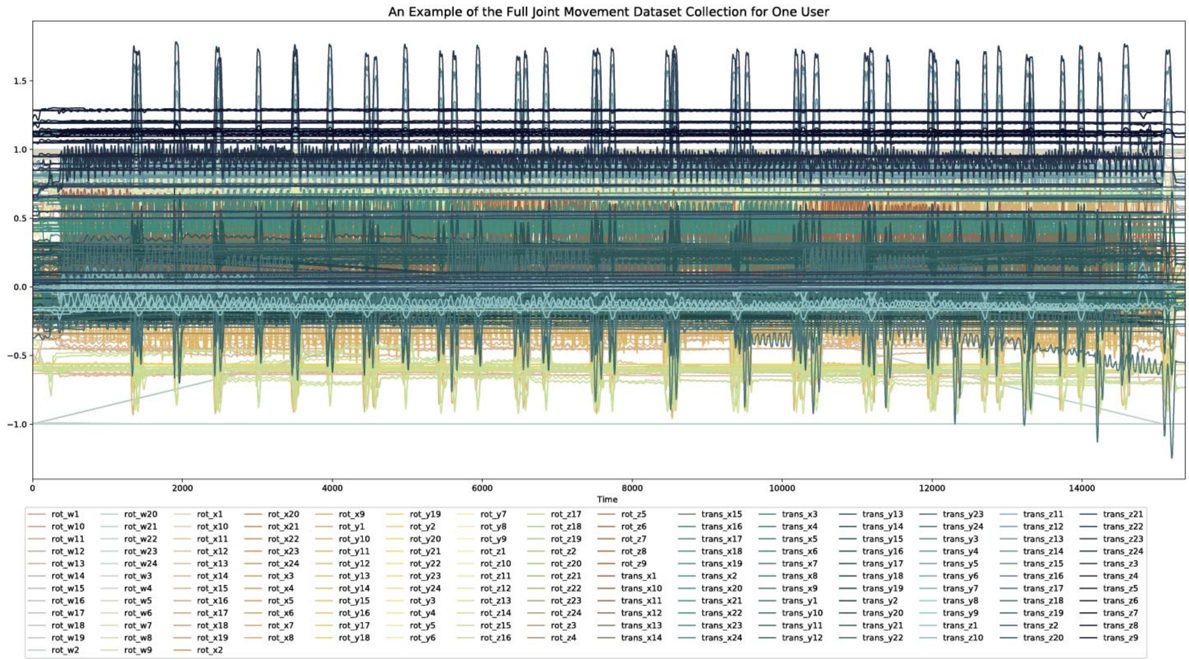


Figure 3.5: An example of the full reaching movement dataset collection for one user is shown in this Figure. It illustrates all the repetitions recorded for each cell from each joint frame using the X-sens Suit. For each joint frame, the translation **(X, Y, Z)** and rotation **(X,Y,Z,W)** are recorded.

Figure 3.5 shows an example of the time-series dataset for just on participant. From this Figure, one can realise the extent of the data collected from just one participant. From every joint frame, the translation and rotation were recorded; therefore, 161 variables made up the time-series dataset. Each of the 23 body segments had its own frame represented by three variables for translation and an additional four for rotations using quaternions. In the legend shown in Figure 3.5 the rotational (x, y, z, w) are referred to as rot_x, rot_y, rot_z and rot_w. The preparation and cleaning of such a dataset were quite intensive and required continuous visualisation methods that ensured that the right reaching movement was extracted from the whole dataset.

Figure 3.6 shows the plot of the right-hand translation reading for one of the participants for the three different starting positions. These illustrations were used as guide to be able to segment, clean and prepare the time-series dataset in an easier way. Preceding the layout of the data collection, we made sure to facilitate the cleaning and preparation of the data by including some visual guides in the data itself. These guides in the data can be seen in the Z position of the right hand in Figure 3.6. Based on the assumption that the right hand will only move above the table on which the board rests, we asked participants to raise both hands between the ten reaching movements for each cell. In this way, we made sure to have a way of segmenting the data collection from the different cells. The Python scripts were written to implement automatic peak detection was used. The peak differences in the Z reading of the right hand were quite different from when the user was doing the reaching movement. Therefore, this automatic peak detection worked perfectly to separate the different cells. Although this was extracted automatically, a visual verification before segmenting the time series dataset was implemented for each of the 450 reaching movements for every participant. The X translation shows that the distance between the starting position and the cells was more when starting from position three (subplot 3.6B - participant's leg) when compared to starting position one (subplot 3.6A - table), provided that the latter starting position was close to the board itself. From the X translation, it is visible that there are five cells in each row (three rows in total). From the Y translation, it can be seen that the five cells are next to each other.

Figure 3.7 depicts exactly where the ten repeated reaching movements are from the sub-figure 3.6B. For clarity, the repeated ten reaching movement are marked with the colour coded markers. Additionally, the hand-up between the different cells (differ color markers) is marked on the Z translation. As stated in Figure 3.6, $cell_5$, $cell_{10}$ and $cell_{15}$ are the far right cells on the board and, therefore, closest to the right hand. Figures 3.6 and 3.7, illustrate this through the lowest magnitude along the Y translation for the reaching movement.

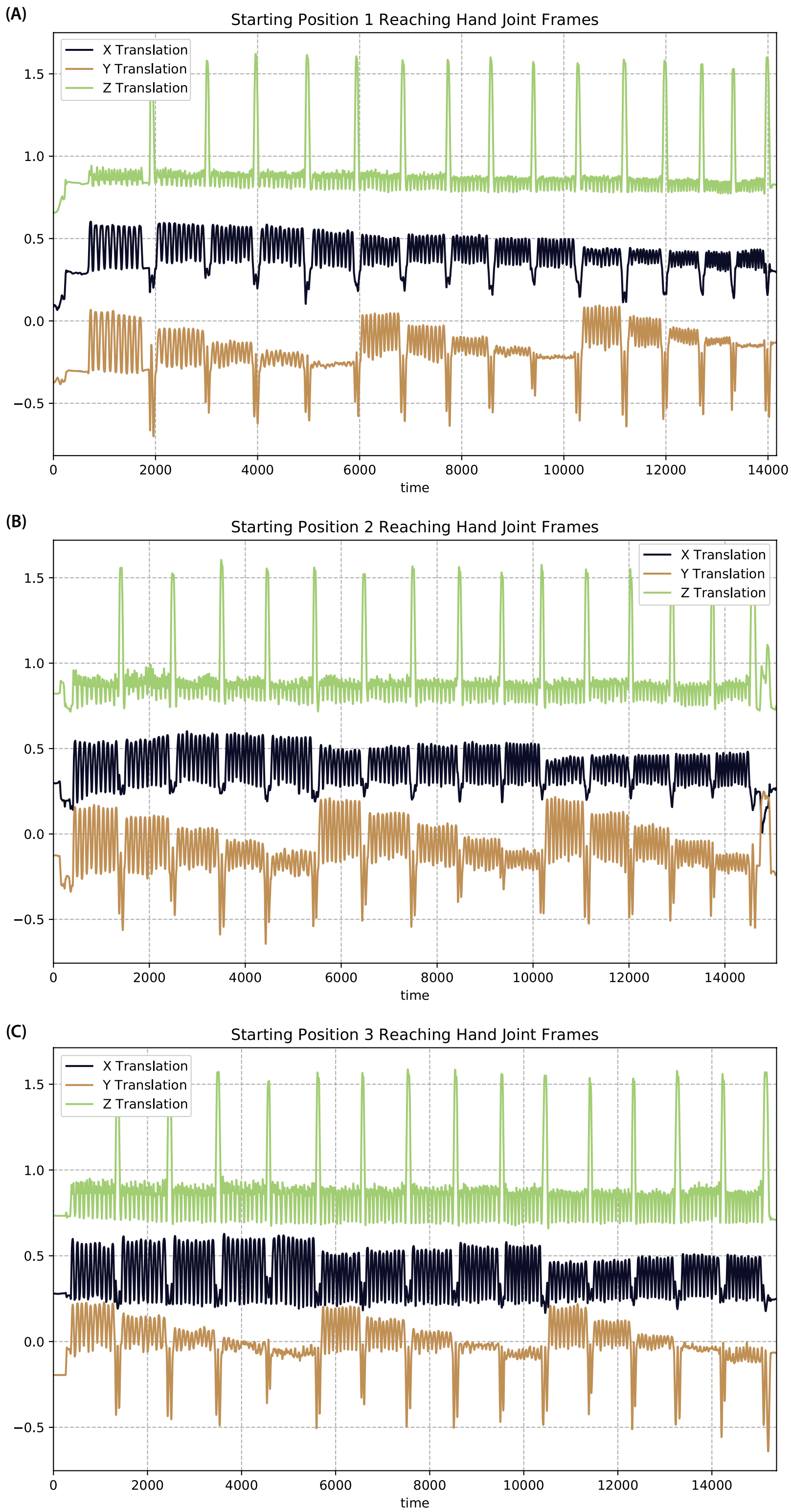


Figure 3.6: The recorded **(X,Y,Z)** of the right hand of one user from the three different starting positions. Sub-figures **(A)**, **(B)** and **(C)** show the **(X,Y,Z)** position of the right hand respectively from the three different starting positions.

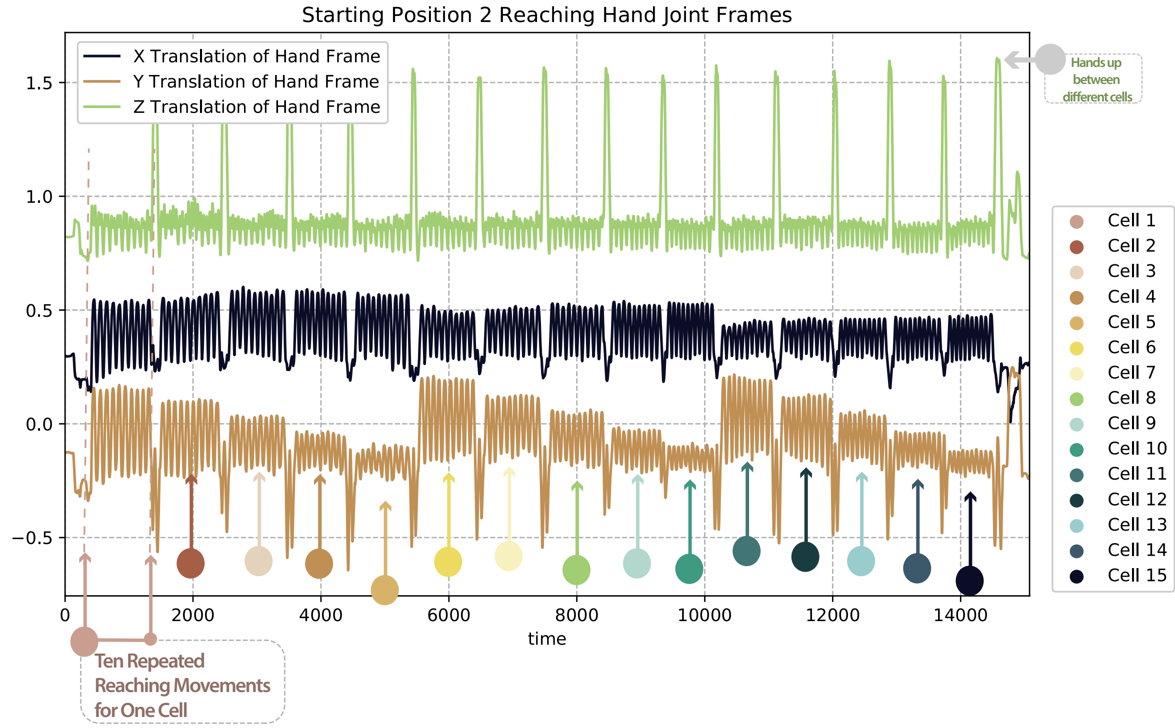


Figure 3.7: An illustration to explain how the full time-series segmentation was implemented based on the projection of the recorded **(X,Y,Z)** of the right hand of each user. The segmentation is required to fully separate the ten reaching movements for the 15 cells marked by the circular markers according to the cell legend on the RHS of the Figure.

After segmenting the different sets of reaching movement for each cell, we are left we subsets of 10 reaching movements for the same cells. Figure 3.8 shows these ten repeated reaching movements segmented from the rest of the 15 cells. An automatic peak detection algorithm was implemented in Python scripts to these data subsets. However, as shown in Figure 3.8, the peak detection in this segmentation failed to generalise for all the participants by simply adjusting the parameters. Therefore, a Python script was developed to capture the x-position of the cursor in the time series translation, enabling the extract of the start and finish points of the ten reaching movements. This manual extraction and labelling process had to be repeated for the 450 time-series segmentation, similar to the one shown in Figure 3.8, resulting in a total of 12,150 reaching movements. Once this segmented reaching movement was extracted, visualisation and analysis for prediction could be implemented.

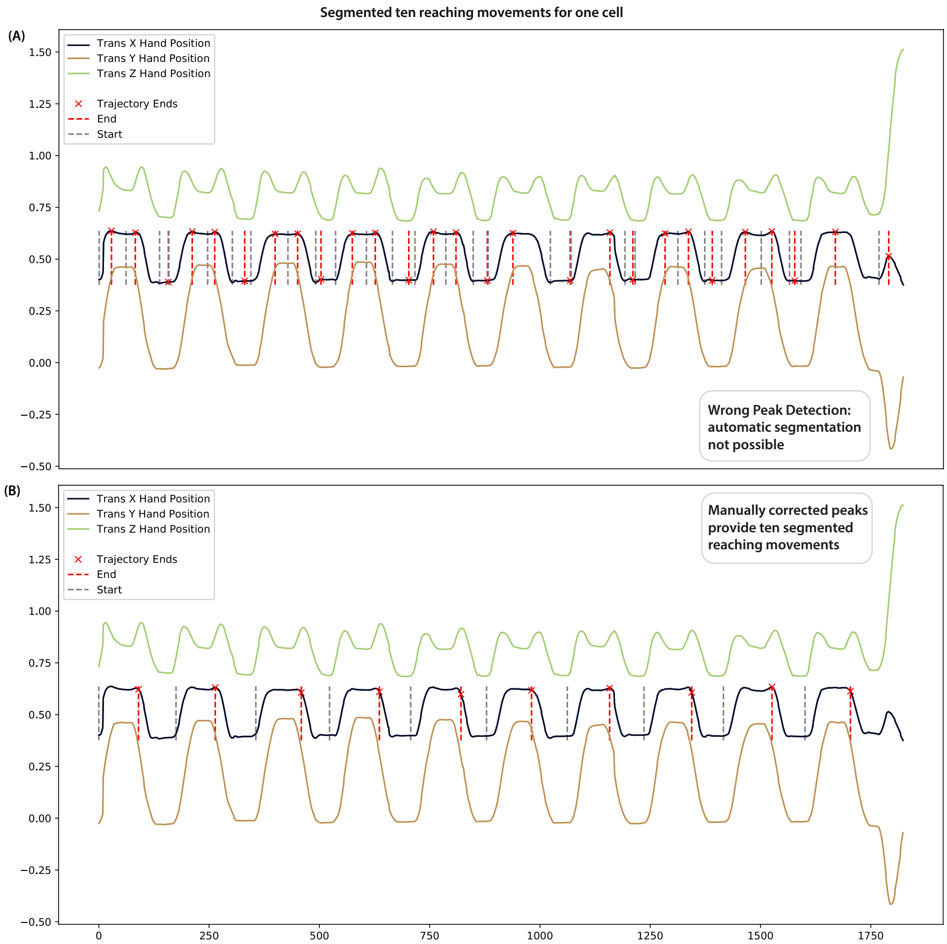


Figure 3.8: An illustration that shows how the segmentation of each reaching movement was implemented based on the projection of the recorded **(X,Y,Z)** of the right hand of each user. This segmentation is required to separate the ten reaching movements from each other after they have already been separated from the other cells. In the illustration, the grey tick marks indicate the start of the reaching movement while the red tick marks indicate the end of the reaching trajectory. It should be noted that the red and grey tick marks were manually corrected on the plotted graphs.

3.3.2 Algorithms

3.3.2.1 Data Representation

The data collected from **CS1** is a time-series segment, specifically for one of the 15 reaching cell positions. Each segment of data is a multivariate time series

$$\{X_t\}, t \in T \tag{3.1}$$

$$x = \{seg_{k_l}(i) : 1 \leq i \leq T, 1 \leq j \leq F_{dims}\} \tag{3.2}$$

With i the time sample index for a segment (one type of reaching movement) and j the dimension index, where T is the number of time samples per segment and F_{dims} is, 23, the total number of joint dimensions of the Xsens Suit. Each participant has a total of K segments, with each data segment seg having a label from $1 \leq l \leq 15$. Therefore this means that if an appropriate time-series clustering algorithm had to be applied to our reaching movement dataset, the number of clusters C_k will be required to be equal to $k = 15$ and $C_m \cap C_n = \oslash$ for $m \neq n$ for the whole time-series dataset $x = \cup_{m=1}^{k} C_m$. In a time-series clustering literature review, Aghabozorgi et al. [6] explain how clustering on such datasets can be implemented in three ways, whole, sub-sequence or time-point clustering. Whole time-series clustering is when the segments of the individual time-series are clustered based on their similarity. Sub-sequence clustering is when a sliding window is used to extract the clusters. Time-point clustering is when a combination of the temporal and values is used to create the clusters. The methodology used to carry out these clustering approaches can either be shape-based, feature-based or model-based [6]. At this stage, we are interested in identifying whether or not the reaching movement is distinguishable at most of the time-series data-point. The underlying assumption is that the final reaching cell on the board cannot be approximated for the initial part of the movement, but it should be more distinguishable as soon as it gets closer to the final reaching cell position. In order to be able to visualise this, the whole time-series clustering is required to visualise all the time-series data-point in one space.

There exist many different approaches that allow clustering. In particular, for time-series datasets, time-series representation, similarity/distance measures, clustering prototypes, and time-series clustering algorithms are the four approaches mainly highlighted in the literature [6]. To verify the sanity of our datasets, we need a dimensionality reduction method that somehow allows the visualisation of the 15 reaching cells on the same manifold to allow comparison at the different data points so the time series. In order to be able to do this, dimensionality reduction methods used the form of similarity measure to be able to perform dimensionality reduction. The two approaches of dimensionality reduction implemented here are PCA, which uses Euclidean distance measures, and t-SNE represents the distance between points to probabilities.

3.3.2.2 Principal Component Analysis

PCA, is a linear dimensionality reduction method which is commonly used to obtain the general information content from a multivariate time series x for each movement. This methodology transforms input data to a lower dimensional manifold which in turn facilities visualisation [23] and feature extraction [50] by identifying variation in movements while ignoring noise [113] in the high dimensional input data. The data is prepossessed as described in the previous section by removing anything that is not a reaching movement toward the cognitive game board and correcting the shift through the pelvis frame along every participant. The reaching movement data is centring along all reaching movement dimensions by removing each mean value from the dimension and scaling back.

In these analyses, the reaching movement data is a matrix $[seg_{i,j}]_k$ of dimensions $T \times F_{dims}$ for each segment k. PCA provided the eigenvectors $y_{k,i}$ on each of the grouped k matrices for each participant along the i-th principal direction. The PCs are ordered in decreasing eigenvalues variance $\lambda_{j,i}$, from the first dimension until the last PC with

$$\frac{\lambda_{j,i} - \lambda_{j,(i+1)}}{\sum_{i=1}^{T} \lambda_{j,i}} > \lambda \tag{3.3}$$

This threshold provides T-dimensional eigenvector that projects the data into its principal components. The principal components are the mean projections of the input matrix on the eigenvectors obtained through the PCA. The threshold set on y defines the total number of PC dimensions to keep as per equation 3.3. This threshold will provides the spatial variance of the reaching movement with the compound PCs p projection transforming the collected input data $x(l)$ into a collection of PCs which form a manifold surface $\mathcal{M}_p$.

3.3.2.3 t-Distributed Stochastic Neighbor Embedding

Unlike the PCA, the t-Distributed Stochastic Neighbor Embedding (t-SNE) is a non-linear dimensionality reduction method suitable for easier visualisation of high dimensional complex datasets. The main drawback of PCA is that it is not able to interpret complex polynomial relationships between features. Any human movement, in particular reaching movement, can be dynamically explained in an interrelation of polynomials in space, that is, a curved manifold. The t-SNE can retain the local and global structure of the dataset, unlike most of nonlinear techniques. As a technique, it aims to map close points nearby in the low-dimensional representations and also map distant points to distant points while preserving the geometry.

The SNE method tries to minimise the dissimilarities of the two conditional probabilities, one for the data point in the high dimensional space and one for the low dimensional space. The conditional probability for the high-dimensional data-points is given by:

$$p_{r|q} = \frac{e^{\frac{-\|h_q - h_r\|^2}{2\sigma_q^2}}}{\sum_{k \neq q} e^{\frac{-\|h_q - h_k\|^2}{2\sigma_q^2}}} \tag{3.4}$$

The low-dimensional data-point are l_q and l_r and therefore the conditional probability for this space is provided by:

$$q_{r|q} = \frac{e^{\frac{-\|l_q - l_r\|^2}{2\sigma_q^2}}}{\sum_{k \neq q} e^{\frac{-\|l_q - l_k\|^2}{2\sigma_q^2}}} \tag{3.5}$$

where the σ_q is the variance of the t-distribution centred over each high dimensional input data feature x_q. The σ_q is not unique since it cannot be an optimal value for all data points due to varying densities across the whole dataset. In dense regions of the curved manifolds, a small σ_q is a better representation of the variance in the data than in sparser regions. All the values of σ_q are obtained through a binary search and form a probability distribution P_q. This P_q distribution provides the perplexity, which is a parameter to the t-SNE. The perplexity limits the number of effective neighbours and the minimization of this cost function is performed through gradient descent. The perplexity is defined as:

$$Perp(P_q) = 2^{H(P_q)} \tag{3.6}$$

where $H(P_q)$ is the Shannon entropy of P_q given by:

$$H(P_q) = -\sum_r p_{r|q} log_2 P_{r|q} \tag{3.7}$$

These conditional probabilities are aimed to model pairwise similarity, and therefore when $q = r$ the conditional probability is set to zero. The main difference between the SNE and the t-SNE is the minimization approach of the sum of differences of the conditional probability. The t-SNE uses a symmetric version of the SNE cost function (Kullback-Leibler divergences) which is computationally more efficient

The drawback of using the t-SNE technique is that when a multivariate datasets is mapped to a lower dimensional space cannot be constructed back to the input features. Thus such techniques are mainly a visualization tool, and non-inference can be based only on the t-SNE lower dimensional space.

3.3.2.4 Distance Measures

The outcome of the dimensionality reduction methods explained above highly depends on their methodology's underlying distance measure approach. The most appropriate distance measure highly depends on the time-series dataset and whether or not there are challenges of noises, offset translation, longitudinal scaling, linear drift, discontinues, and temporal drift. The data preparation and cleaning explained in section 3.3.1 aimed to take care of offset, translation, linear drift and discontinues in each of the reaching movement segments extracted as shown in Figure 3.8. The temporal shift and different temporal speeds of the reaching movement that make up each segment K cannot be corrected because they are characteristics of how humans move in space. These characteristics indicate that the similarity in our reaching movement dataset is ideally found in the shape and structural change between data-point and not in time.

There are four types of distance measures: shape-based, comparison-based, features-based and model-based. Shape-based measures use time and shape to extract the similarity, for example, Euclidean, DTW, Longest Common Sub-Sequence(LCSS), and Minimal Variance Matching (MVM) [62, 163]. Compression-based similarity examples are cosine wavelets, Pearson's correlation coefficient and Piece-wise normalisation. Feature-based measures are used only for long time series in statistics, whereas model-based measures, such as Hidden Markov Models (HMM)[84, 112, 156], are used for more extended datasets.

Out of these, the Euclidean distance and DTW are the most prominent methods of distance measures. Euclidean can work with some of the time-series datasets; however, the DTW outperforms in most cases when it comes to a dataset that requires an elastic distance measure due to unequal clustering. These similarity measures are often combined with clustering approaches so that no information in the data is overlooked [90]. Additionally, the authors indicated that to handle the shifts in time, DTW is required as a step in clustering [169]. The authors, Aghabozorgi et al., [6] highlight that the challenges of a time-series dataset can fail in the most conventional clustering algorithms and that it is essential to understand what the potential clusters in the data can represent.

3.3.3 Probabilistic Movement Primitives (ProMPs)

As the literature shows, ProMPs are more efficient for collaborative tasks when compared to DMP[53] [101] [118]. The error in prediction is far lower in ProMP, as well as they provide the ability to do inference learning and to know the correlation between the input and the train ProMP.

3.3.3.1 Learning Probabilistic Movement Primitives for the Reaching Movement

The ProMP is modelled as Bayesian parametric models of the recorded reaching movement trajectories in the form:

$$\xi(t) = (\Phi_t)w + \varepsilon_\xi \tag{3.8}$$

where $w \epsilon R^M$ is the time-independent parameter vector. This vector is the weighted RBFs where Φ is a vector of M radial basis functions evaluated at time t. The $\epsilon_\xi \sim \mathcal{N}(0, \beta)$ is trajectory noise.

The vector of M radial basis functions will be tuned during training. This is represented by the following equation:

$$\Phi = [\psi_1(t), \psi_2(t), ...\psi_M(t),] \tag{3.9}$$

where

$$\psi_i(t) = \frac{1}{\Sigma_{j=1}^{M} \psi_j(t)} exp^{(\frac{-(t-c(i))^2}{2h})} \tag{3.10}$$

$$c(i) = i/M \tag{3.11}$$

$$h = 1/M^2 \tag{3.12}$$

For each reaching trajectory, the weighted parameter vectors need to be computed to minimize the error between the observed trajectory and the Bayesian parametric model itself. The algorithm used to do this is a Least Mean Square algorithm. To avoid having a matrix of weights that is not inverted a diagonal term is added, and Ridge Regression is performed. This is done through:

$$w_i = ({\Phi_t}^T \Phi_t + \lambda)^{-1} {\Phi_t}^T \xi_i(t) \tag{3.13}$$

The above weights are used to compute the Normal Distribution:

$$p(w) \sim \mathcal{N}(\mu_w, \Sigma_w) \tag{3.14}$$

where

$$\mu_w = \frac{1}{n}\sum_{i=1}^{n} w_i \tag{3.15}$$

$$\Sigma_w = \frac{1}{n-1}\sum_{i=1}^{n}(w_i - \mu_w)^T(w_i - \mu_w) \tag{3.16}$$

What the ProMP does is that it captures the distribution over the observed reaching trajectories. Each reaching trajectory is represented by the movement primitives, and the mean of the distribution is used to represent each of the 15 reaching ProMP created.

3.3.3.2 Predicting Reaching Movement from Partial Observations

Once these ProMPs are created, it can be assumed that the observed reaching movements ($\Xi^o = [\xi^o(1),...,\xi^o(n_o)]$) will follow these learned distributions. This hypothesis is valid, provided that enough movement data is collected. When collecting the dataset for CS1, we ensured we had enough data samples. The goal is to predict the reaching trajectory after n_o observations for an estimated time $\hat{t}_f$ for the rest of the predicted trajectory $\hat{\Xi}$. The learned prior distributions are taken and updated to give $p(\hat{w}) \sim \mathcal{N}(\hat{\mu}_w, \hat{\Sigma}_w)$ from the following equations:

$$\hat{\mu}_w = \mu_w + K(\Xi^o - \Phi_{[1:n_o]}\mu_w) \tag{3.17}$$

$$\hat{\Sigma}_w = \Sigma_w - K(\Phi_{[1:n_o]}\Sigma_w) \tag{3.18}$$

Where K is a gain computed through marginal and conditional distributions:

$$K = \Sigma_w \Phi_{[1:n_o]}({\Sigma^o}_\xi + \Phi_{[1:n_o]}\Sigma_w {\Phi^T}_{[1:n_o]})^{-1} \tag{3.19}$$

3.3.3.3 Predicting a One Reaching Movement From All Reaching Movement

When predicting an observed trajectory in real context, a time modulation parameter $\hat{a}$ is needed. There are different methods that can be used to estimate the time modulation, either using the mean, maximum likelihood, minimum distance and other criteria. Time modulation is implemented by dynamic time wrapping (DTW). In this socially aHRI the number of ProMPs are 15, and the assistive robots need to be able to select one. This is done by using minimizing the distance between the early observation and the mean of the ProMP for the first portion of the trajectory:

$$\hat{k} = argmin_{k\in[1:K]}\left[\frac{1}{n_o}\sum_{t=1}^{n_o}\left|\Xi_t - \Phi_{\hat{a_k}t}\mu_{w_k}\right|\right] \tag{3.20}$$

After this is computed, Equations 3.17, 3.18 and 3.19 are used to update the posterior distribution and the inferred trajectory is given based on :

$$\forall t \in [1 : \hat{t}_f], \hat{\xi}(t) = \Phi_t \hat{\mu}_{w_k} \tag{3.21}$$

The training of the ProMP was implemented based on a library built through the work of Dermy et al. [42].

3.4 Results

3.4.1 Visualisations of the Cleaned Reaching Movement Dataset

Figure 3.9 shows an example of the segmented reaching movement data after the process described in section 3.3.1. Each column in Figure 3.9 shows the trajectories from a different starting position, whereas each row shows the right hand's X, Y and Z position. From the $X(m)$ plot, it can be seen that there is a group of 5 cells in each row. $cell_1$ to $cell_5$ top row, $cell_6$ to $cell_{10}$ middle row, and $cell_{11}$ to $cell_{15}$ bottom row.

Such plots are required to know if there is a need to correct the reference frame of the human posture. By looking at the data, it was observed that the Xsens Suit recordings could sometimes show a drift from the calibrated reference frame. Correcting any shift or drift depends on the methodology used for visualising and predicting the reaching movement. Some methodologies require data scaling, and others do not, but it is essential to keep this in mind. During the experiment, the chair's position relative to the table and board was fixed by markings on the table and floor. Based on this assumption, a general correction was implemented on all joints. By such correction, we assume that the participants' seating position did not change from outside the markings on the floor. The correction was carried out by keeping the pelvis frame fixed to the calibrated reference frame of the Xsens.

Figure 3.10 shows the 3D joint plots of one of the participants while sitting in front of board cognitive game. These figures were visually checked for all the 12,150 reaching movements as a sanity check to verify that the human movement dataset is correct.Sub-Figures 3.10A, 3.10C and 3.10D show the reaching movement of one cell at a random time (t). Sub-figure 3.10 B shows how the human movement in the other sub-figure appears when overlapped on one 3D plot.

To better visualise the reaching movement shown in Figure 3.9, Figure 3.11 is plotted to show the 3D plots for the 450-reaching movements of one of the participants. Figure

3.11A shows all the 450-reaching movements for one participant, whereas, sub-figure 3.11B shows the reaching movement of the top row, that is $cell_1$ to $cell_5$, Sub-figure 3.11C shows the reaching movement of the middle row, that is $cell_6$ to $cell_{10}$, and Sub-figure 3.11D shows the reaching movement of the middle row, that is $cell_{11}$ to $cell_{15}$.

These visual check and plots were necessary to gain a comprehensive understanding of the data complexity and to ensurer its sanity before proceeding with reaching movement prediction. Understanding the data is crucial, particularly when it is collected from a real-world contexts and scenarios involving humans performing the desired movements. The human reaching movement datasets is extensive and requires through examination to ensure that the values obtained from the X-sen suit are accurate and devoid of any misleading information.

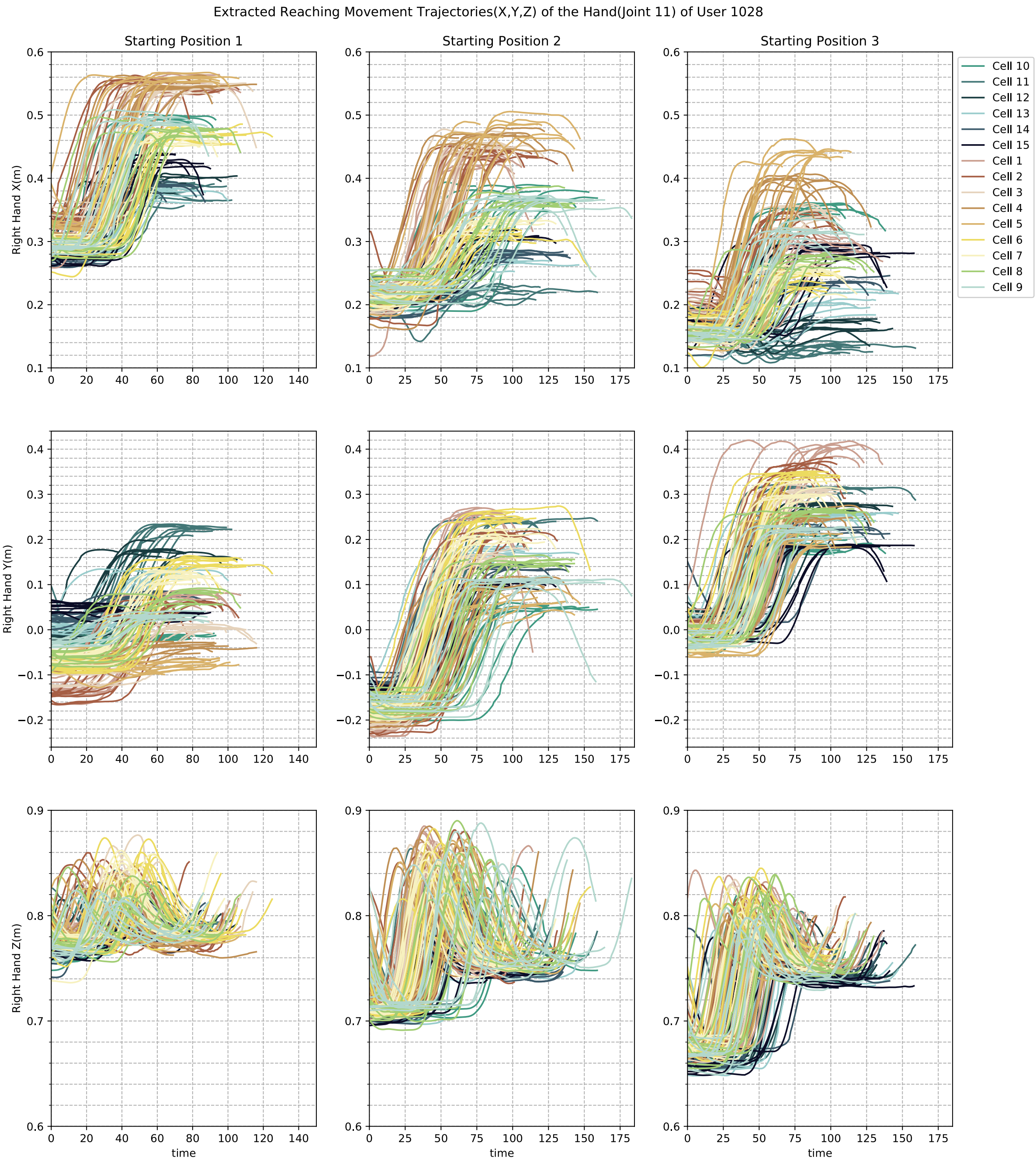


Figure 3.9: 2D plots for the segmented **(X,Y,Z)** Right Hand Trajectories for Participant 1028. The sub-figures in the first column shows trajectories from starting position one, middle column from starting position two and last column from starting position three.

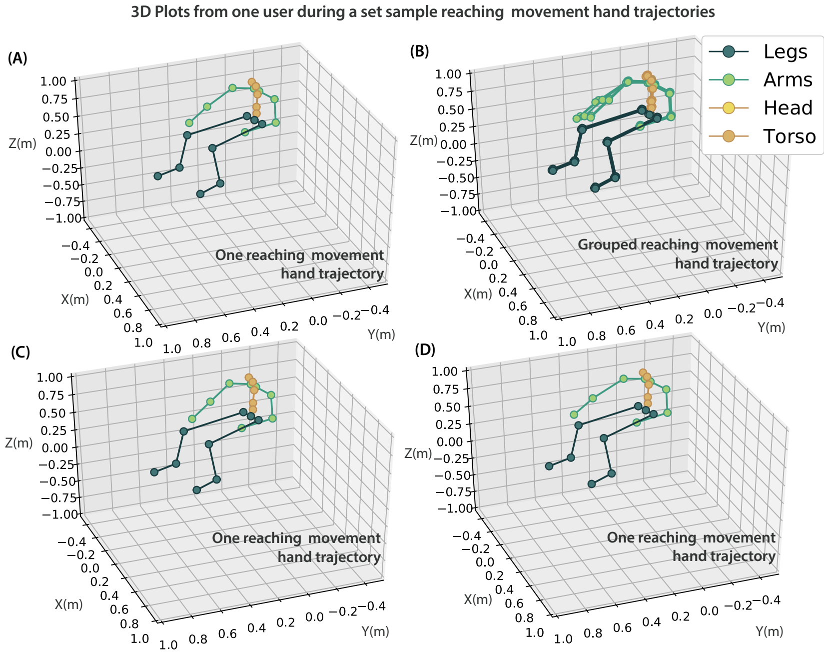


Figure 3.10: 3D joint plots for one user during a reaching movement for one of the cells. Sub-figure **(B)** shows the overlay of sub-figures **(A)**, **(C)** and **(D)** on one 3D plot. Sub-figures **(B)**, **(C)** and **(D)** show a reaching movement at a random time (t) from one of trajectories shown in Figure 3.9.

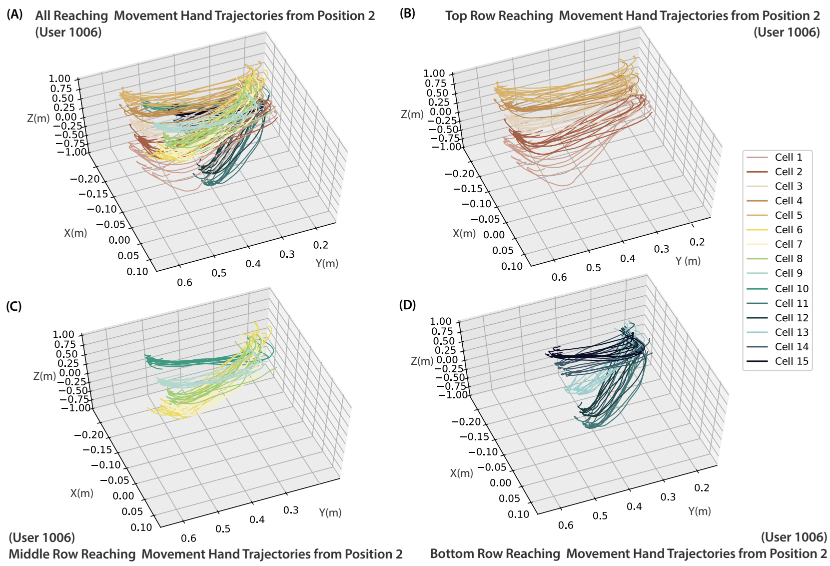


Figure 3.11: Sub-figure **(A)** shows the 3D plots for the segmented **(X,Y,Z)** Right Hand Trajectories from starting position two of Participant 1028. Sub-figures **(B)**, **(C)** and **(D)** respectively show the reaching trajectories for the top, middle and bottom rows.

3.4.2 Visualisations of the Reaching Movement Dataset

To visualize the reaching movement data collected from **CS1**, where the target reaching cell varies across 15 different classes representing different positions on the reaching board. Each labelled data x_l class is required to be projected onto 2-dimensions according to the leading principal components. Each colour projection in this 2D space represents a complete reaching movement, labelled according to the corresponding cell colour. Figures 3.12, 3.13, 3.14, 3.15, 3.16 and 3.17 show the PCs for the reaching segments of each participant separately. The remaining visualization of the PCs for the other participants can be found in appendix A.

Immediately the first aspect visualised through the PCs is that the data point with standard labels, meaning the reaching movement for each cell, are clustered closely together. The projection on the 2D manifold shows that this dataset is non-linear since the 15 clusters created are not distinct. The clusters overlap each other for the initial part of the trajectory, however, when the arm is closer to the cell there is a distinction on the manifold between the different final reaching positions. On these manifold, there is a resemblance in how the three different rows project on the manifold. The dimensionality reduction for each participant is vital to verify the sanity of the dataset after cleaning and preparing the original and raw data collected during the experiments. The projection on this 2D space is necessary to compare the similarity between each participant on common ground.

The visualisation of the PCs hints at the fact that prediction of the final reaching movement might need the consideration of non-linear approach to be able to generalise properly between all the different participants. The t-SNE algorithm operates by establishing conditional probabilities between data pairs and aims to minimize the disparity between high and low probability dimensions. This method identifies patterns in the data based on similarities among the multivariate features, revealing clusters within the reaching movement dataset that are not readily visible in PCA. Unlike PCA, t-SNE performs non-linear dimensionality reduction, comparing conditional probabilities to expose these hidden clusters. This approach delineates soft boundaries between neighboring data points, effectively preserving the global structure and accurately clustering curved manifolds. Such properties allow the Figures 3.18, 3.19, 3.20, 3.21, 3.22 and 3.17 shows the visualisation of selected participants using the t-SNE approach. The t-SNE algorithm shows the clusters according to the final reaching position of the cells. The visualisations are very different from the results obtained through PCA. The main reason is that PCA cannot take care of the dynamic shift in time. PCA does not inherently handle the temporal or sequential aspect of time-series data. It doesn't consider the temporal order or the dynamics inherent in time-dependent data. These results echo the statements made in [6] that additional steps are required prior to clustering. The t-SNE overcomes the unequal segments and time-shifted by looking at the similarity between data features and comparing the lower and higher dimensional probabilities.

The main differences between the two visualisation methods expose the requirements of a times-series dataset for movement prediction. It highlights that each reaching movement must be viewed similarly to all of the other sub-sequences that make up the rest of the reaching movements. These similarity bases are required to look at each movement in the same way, irrespective of how much time samples it takes for the movement to be complete. Some users might have employed different speeds for the different cells on the cognitive game; therefore, the movement's curved manifold can have different data points. The t-SNE approach addresses the similarity and differences in the time-series dataset by looking at the differences in the conditional probability in the higher and lower dimensional space. The PCA fails to do so due to its underlying distance measure that fails to extract similarity in the shape of a time-varying dataset.

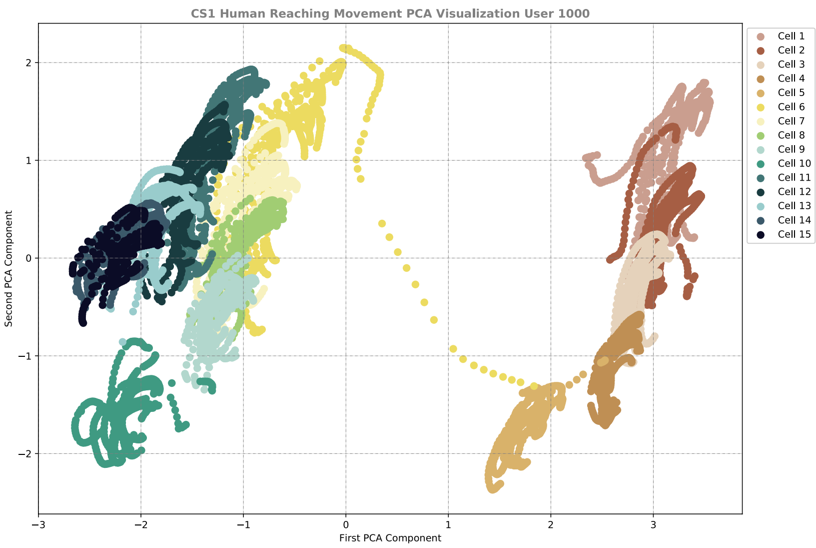


Figure 3.12: Principal components of the Reaching Movement Dataset from Participant 1000. The first two dimensions of the low-dimensional manifold of movements are portrayed here. The colour of each data point is according to the class label of the 15 cells on the board.

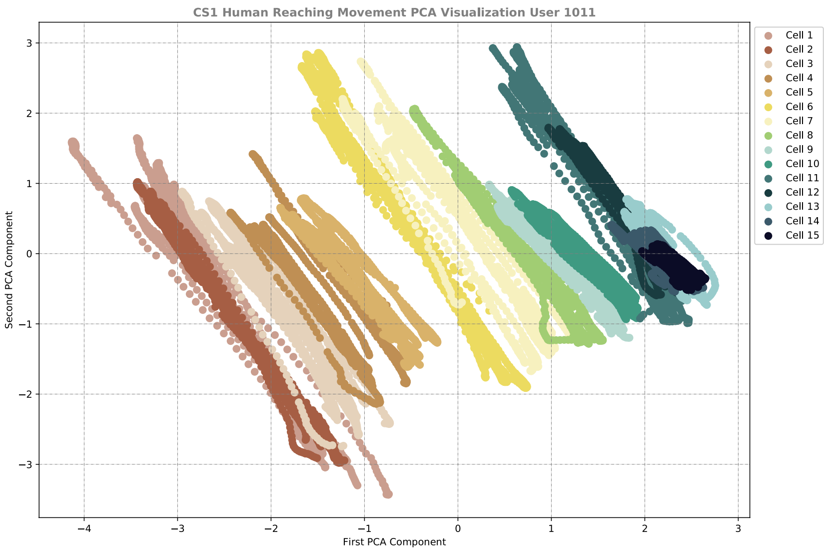


Figure 3.13: Principal components of the Reaching Movement Dataset from Participant 1011. The first two dimensions of the low-dimensional manifold of movements are portrayed here. The colour of each data point is according to the class label of the 15 cells on the board.

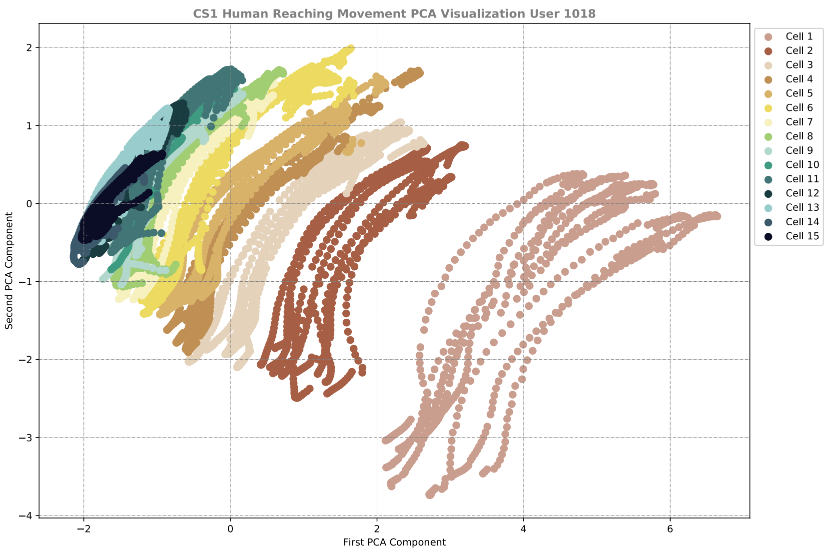


Figure 3.14: Principal components of the Reaching Movement Dataset from Participant 1018. The first two dimensions of the low-dimensional manifold of movements are portrayed here. The colour of each data point is according to the class label of the 15 cells on the board.

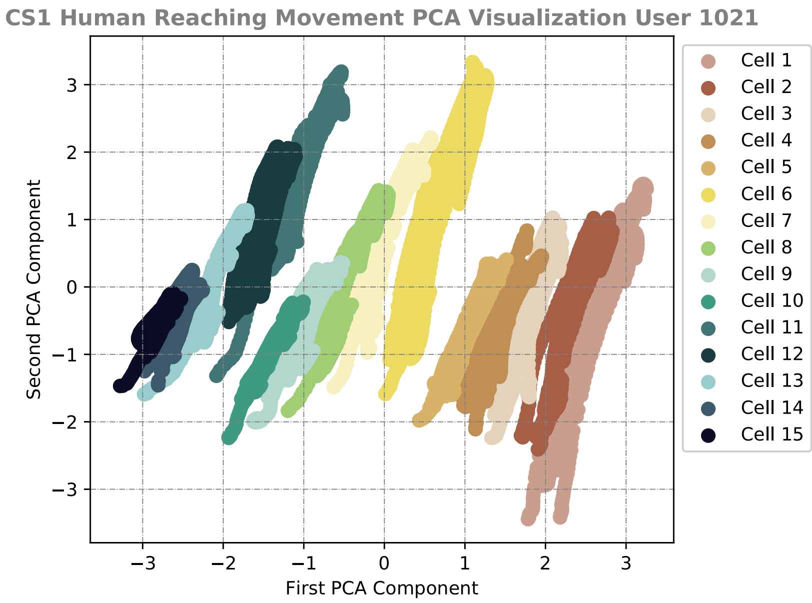


Figure 3.15: Principal components of the Reaching Movement Dataset from Participant 1021. The first two dimensions of the low-dimensional manifold of movements are portrayed here. The colour of each data point is according to the class label of the 15 cells on the board.

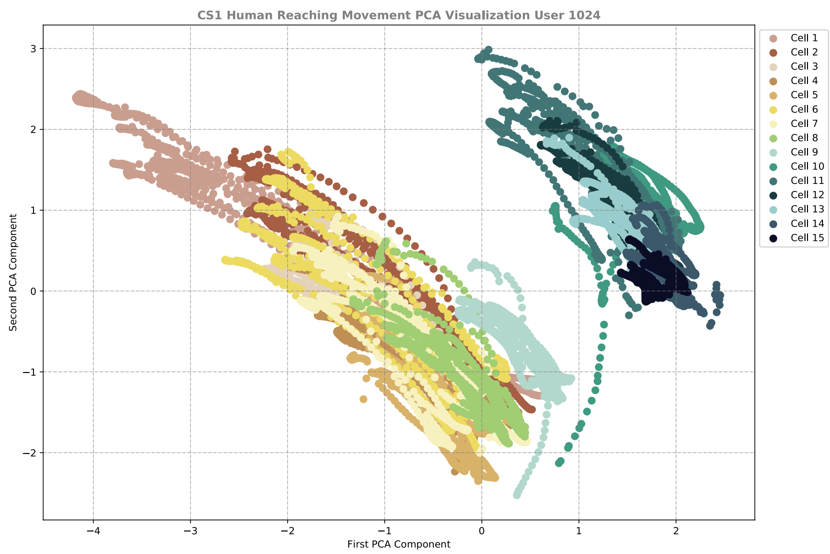


Figure 3.16: Principal components of the Reaching Movement Dataset from Participant 1024. The first two dimensions of the low dimensional manifold of movements are portrayed here. The color of each data point is according to the class label of the 15 cells on the board.

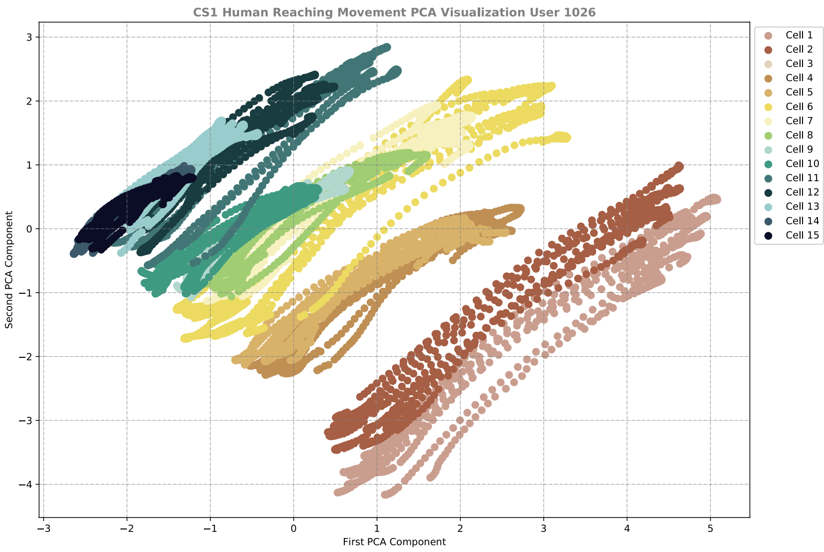


Figure 3.17: Principal components of the Reaching Movement Dataset from Participant 1026. The first two dimensions of the low dimensional manifold of movements are portrayed here. The color of each data point is according to the class label of the 15 cells on the board.

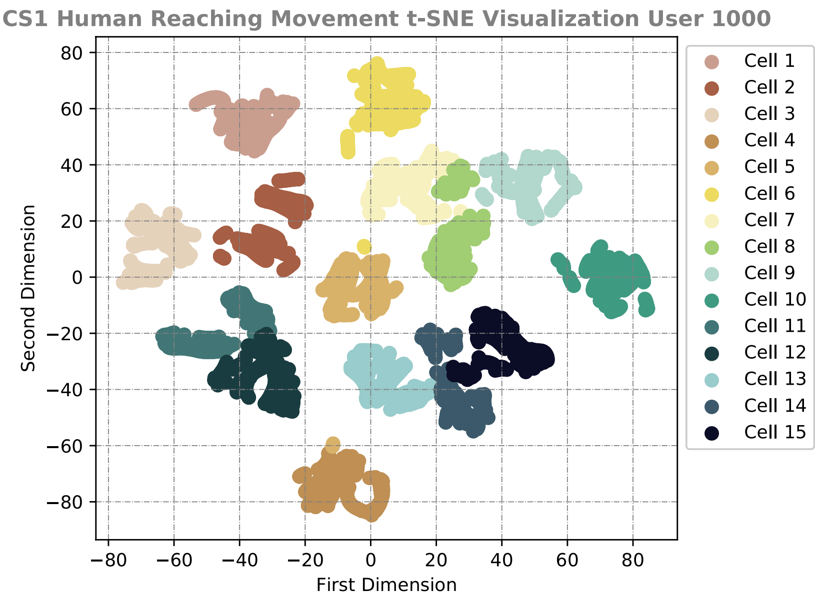


Figure 3.18: t-SNE visualisation of the Reaching Movement Dataset from Participant 1000. The colour of each data point is according to the class label of the 15 cells on the board.

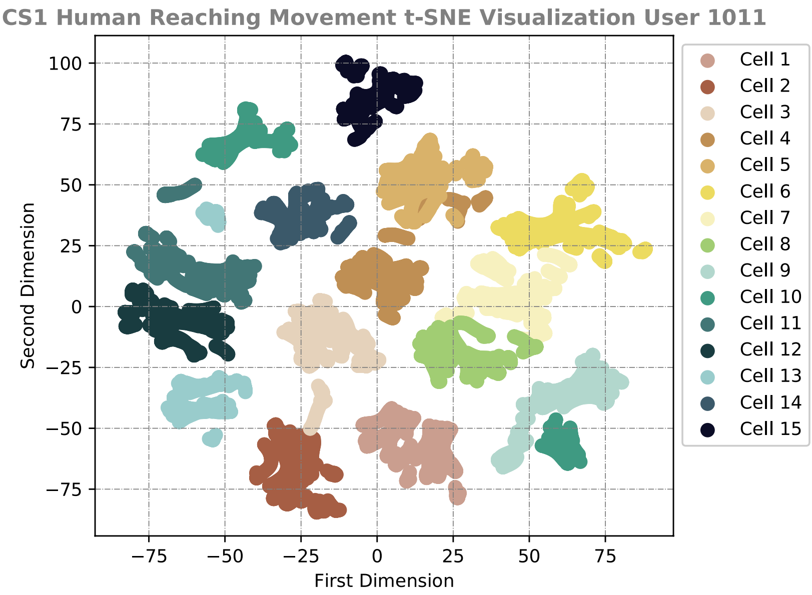


Figure 3.19: t-SNE visualisation of the Reaching Movement Dataset from Participant 1011. The colour of each data point is according to the class label of the 15 cells on the board.

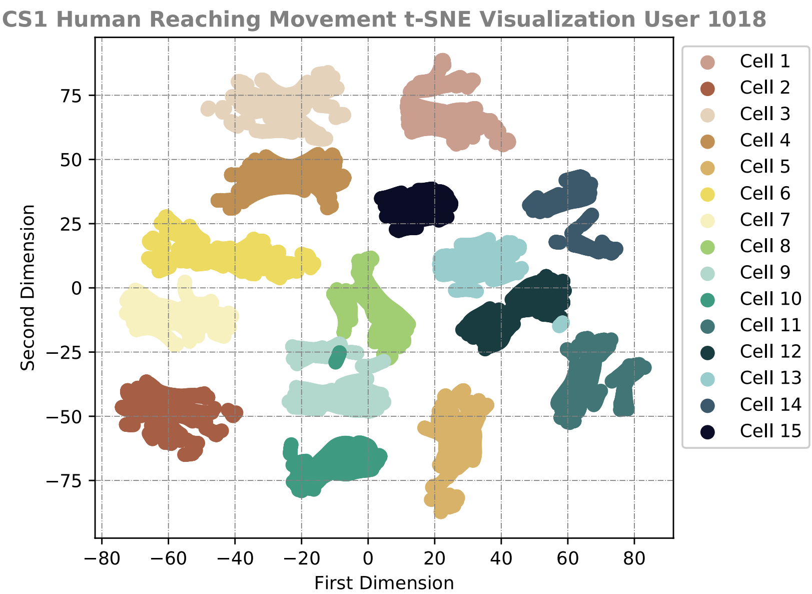


Figure 3.20: t-SNE visualisation of the Reaching Movement Dataset from Participant 1018. The colour of each data point is according to the class label of the 15 cells on the board.

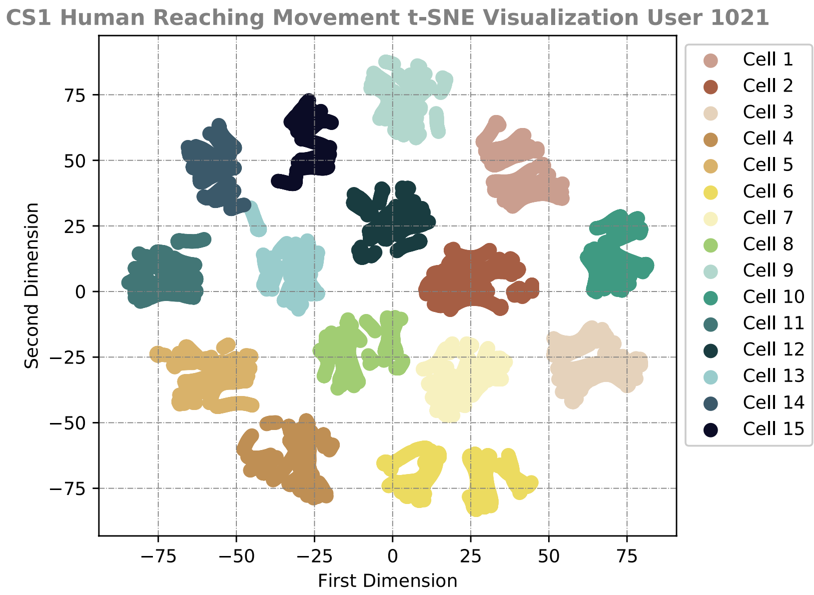


Figure 3.21: t-SNE visualisation of the Reaching Movement Dataset from Participant 1021. The color of each data point is according to the class label of the 15 cells on the board.

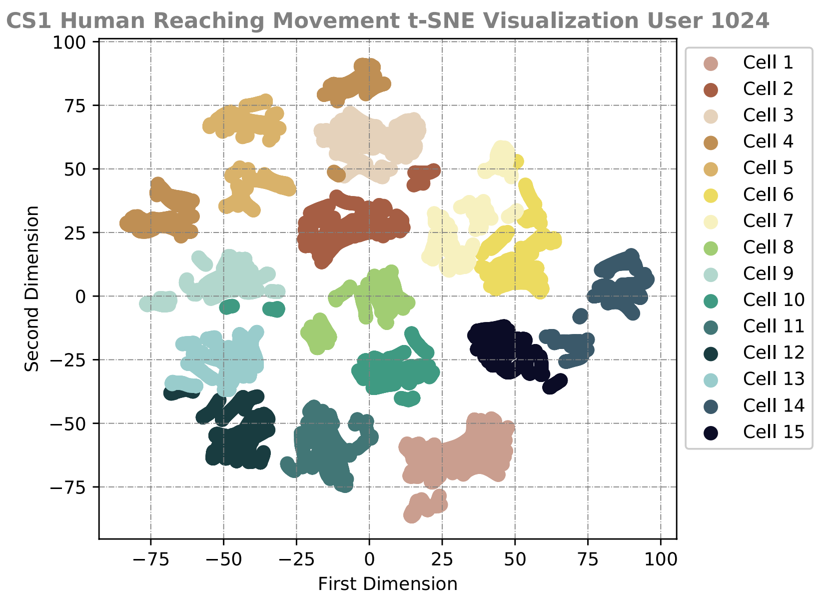


Figure 3.22: t-SNE visualisation of the Reaching Movement Dataset from Participant 1024. The color of each data point is according to the class label of the 15 cells on the board.

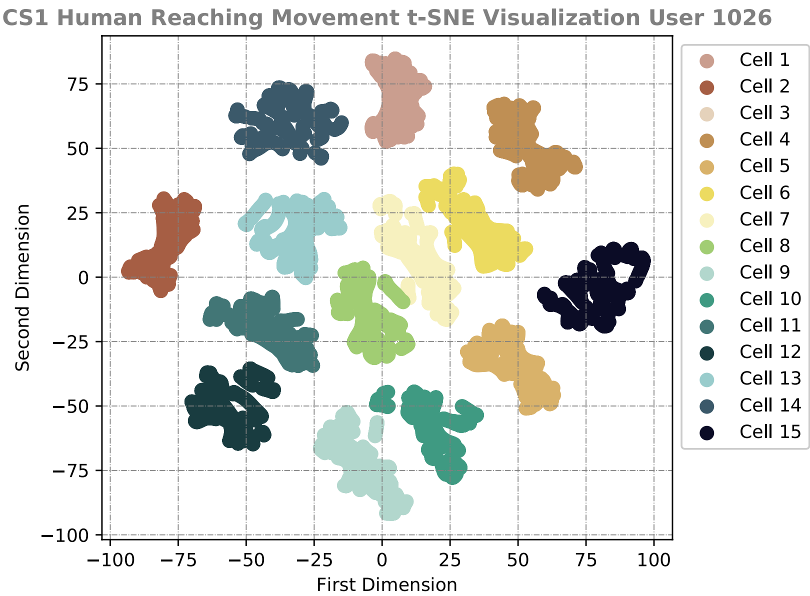


Figure 3.23: t-SNE visualisation of the Reaching Movement Dataset from Participant 1026. The color of each data point is according to the class label of the 15 cells on the board.

3.4.3 Reaching Movement Prediction with Probabilistic Movement Primitives

In the previous section, it was verified that the different reaching movement from the participants can be distinguished from each other as long as the non-linearity and relationship between data points are preserved. However, as per the final objective of this thesis and the chapter itself, ensuring physical safety is essential. The research questions defined in section 3.1.1 aim to answer how these different reaching movements can be easily distinguished in the shortest possible time to ensure physical safety. In order to answer these research questions the prediction of reaching movement is tested using the ProMPs methodology.

Figure 3.24 shows the top view of the cognitive game board. This illustration provides a more detailed explanation of Figure 3.3 displaying the colour-coded cells representing the final reaching goal of each participant. In order to ensure physical safety, it is crucial to predict the reaching goal for each of these different cells before they come too close to the socially assistive robot. The visualisation presented in section 3.4.2 involves projecting a dimensionally reduced trajectory onto a space. In this section, as a fulfilment to the research question posed in section 3.1.1 we present a way of identifying the final reaching cell based on only partial observation of the trajectory.

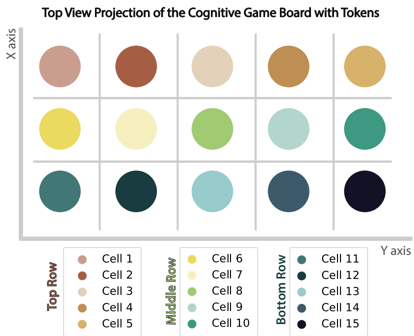


Figure 3.24: The top view of the cognitive game board with respect to the Xsens suit calibration frame. The way reaching movement segments are grouped determines what regions or cells the ProMPs will be able to predict.

3.4.3.1 Learning the reaching movement ProMPs

In order to be able to predict reaching movement for each cell, ProMPs rely on predefined learning models that determine the extent to which they can make accurate predictions. In other words, to correctly predict each cell correctly with high confidence, we need to determine the minimum percentage of the observed trajectory required for accurate prediction. If it results that a high percentage of the trajectory needs to be observed to obtain a high confidence in predicted the cell, it would mean that a longer observation time is required before the socially assistive robot can determine the intentions of the older adult. This longer observation time starts when the older adult begins to move his right arm towards the workspace. If this situation occurs, physical safety cannot be guaranteed in such an interaction context.

In order to compromise between accuracy and observation time, it is necessary to investigate the effect of grouping a set of reaching trajectories and learning them with ProMPs. Grouping the trajectories enables the grouping of regions on the cognitive game board (for reference see Figure 3.2). This grouping can lead to higher confidence in predicting the correct region in a shorter time. Therefore, physical safety can be achieved by correctly predicting the regions on the board and subsequently refining the prediction as time progresses, utilizing a set of trained ProMPs for the individual cells.

The evaluation of grouping the reaching movement trajectories is presented in Figures 3.25, 3.26, 3.27, and 3.28. Figure 3.25 shows the learned probability distribution for grouped reaching movement of one user. The grouping was implemented to all the reaching movement of this user along the three different rows. The top three ProMPs represent the learned probability distribution for the right-hand x-axis movement. These ProMPs demonstrate that, regardless of the percentage of the observed trajectory, they can effectively differentiate between the three rows. However, the bottom three ProMPs, which represent the learned probability distribution for the right-hand y-axis movement, exhibit higher variance, making it practically impossible to differentiate between the three rows based solely on this degree of freedom.

Similarly, Figure 3.26 and Figure 3.27 shows the grouped reaching movement for the same user along the five columns. The top three plots ProMPs show the learned probability distribution for the right-hand degree of freedom along the x-axis of the board. The bottom three ProMPs depict the learned probability distribution for the right-hand degree of freedom along the y-axis of the board. Contrary to Figure 3.28, both Figure 3.26 and Figure 3.27 demonstrate that when grouping the columns the greater difference observed in the ProMPs is across the y-axis, as each column has different values in the y-dimension but similar values along x-axis.

Figure 3.28 illustrates the different ProMPs when grouping reaching movement trajectories based on the different starting positions. The target cell of the reaching trajectories shown is all the same, cell 1.

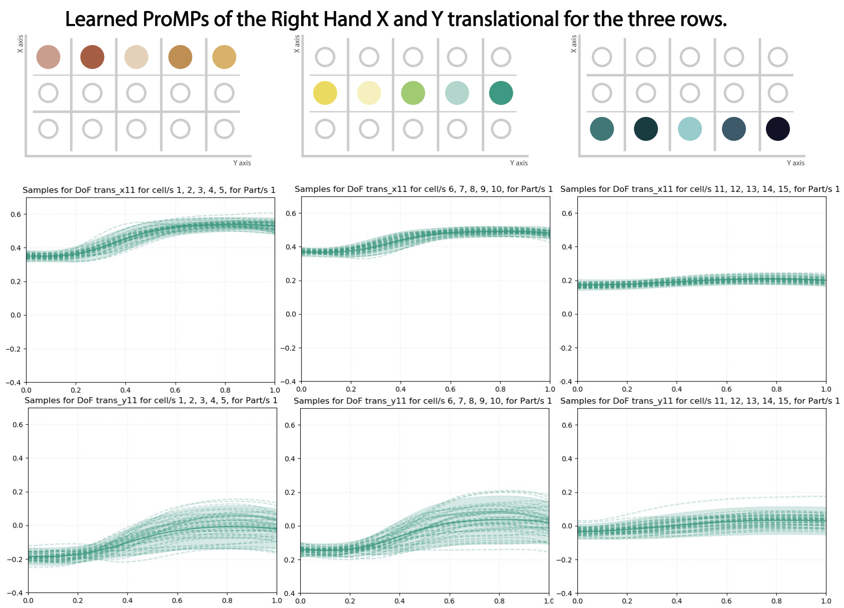


Figure 3.25: Trained ProMPs for one user, grouping reaching movement for each row. The top illustrations highlight the rows from which the reaching movement segments were selected and grouped.

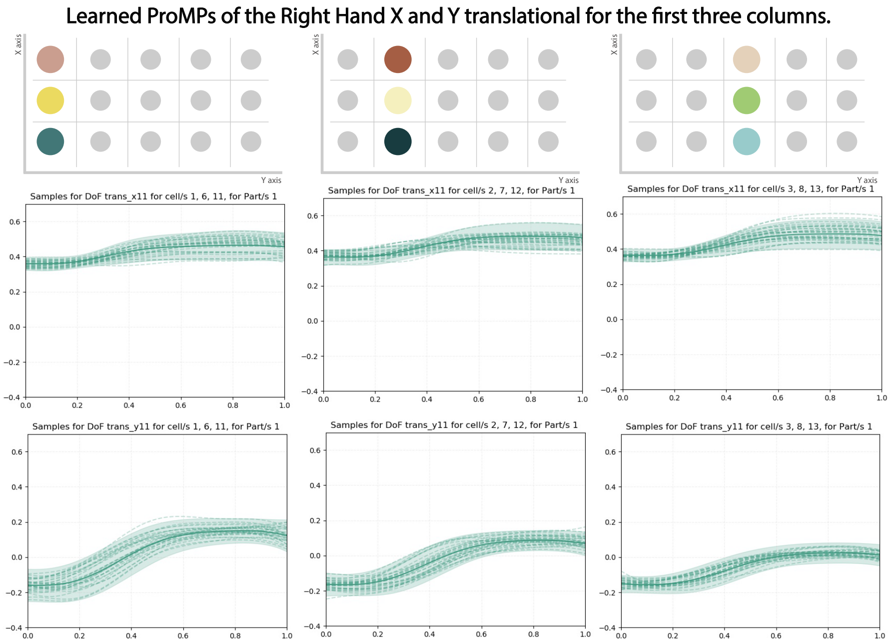


Figure 3.26: Trained ProMPs for one user for the grouped reaching movement for the first three columns. The top illustrations highlight the columns from which the reaching movement segments were selected and grouped.

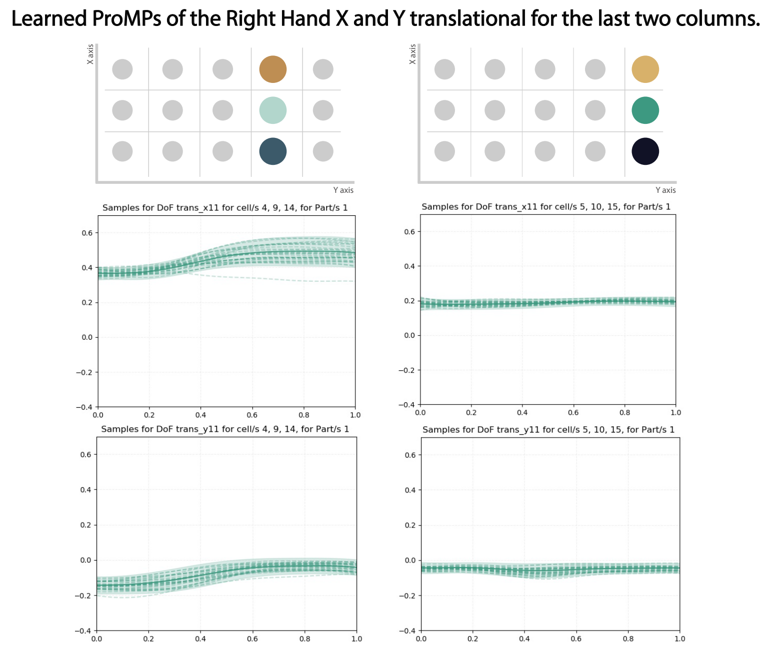


Figure 3.27: Trained ProMPs for one user for the grouped reaching movement for the last two columns. Top illustrations highlight the columns from which the reaching movement segments were selected and grouped.

Sub-figure 3.28*A* shows the ProMP for cell 1 from starting position one. Sub-figure 3.28*B* shows the ProMP for cell 1 from starting position two. Sub-figure 3.28*C* shows the ProMP for cell 1 from starting position three. Sub-figure 3.28*D* shows the ProMP for cell 1 for the grouped starting positions one and two. Sub-figure 3.28*E* shows the ProMP for cell 1 for the grouped starting positions two and three. Sub-figure 3.28*F* shows the ProMP for cell 1 for the grouped starting positions one, two, and three. The target reaching position at the 1.0 (100% of the observed trajectory) is similar in all three parts. However, the most noticeable difference can be observed in the plot showing the ProMP with a starting position three. This position required the participants to start with the arm resting on the leg, whereas starting position one and two were more or less similar along the y-axis. The grouping of the different parts reveals that the ProMP allows for more variability in the probability distribution. This increased variance can make the prediction of the reaching movement more challenging, as it can lead to the wrong prediction of the target cell. However, for ensuring physical safety in all interaction scenarios, it is important to base predictions on realistic datasets. In reality, it is difficult to restrict older adults from choosing where to start playing cognitive games. Therefore, the dataset of CS1 takes on a more realistic approach by considering these different starting positions.

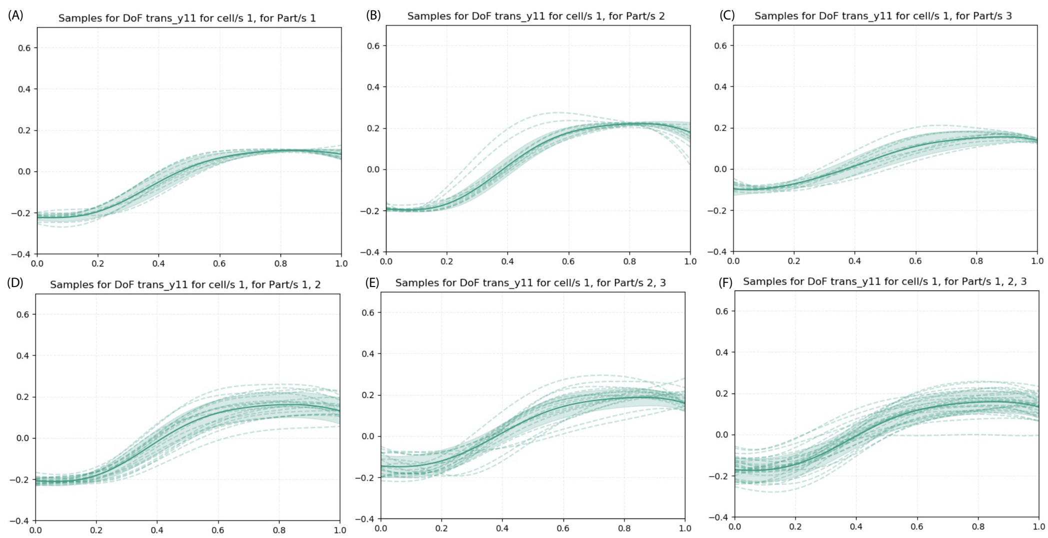


Figure 3.28: Trained ProMPs for one user for the grouped reaching movement from the different starting positions.

3.4.3.2 ProMPs Reaching Movement Prediction Results per User

In this section, a summary and analysis of the results from the human-reaching movement datasets are presented. The objective is to evaluate whether and to what extent the prediction of human reaching movement can be easily distinguished, even between very close cells on the cognitive board game.

While a detailed explanation for one user and one cell will be provided in this chapter, more extensive results can be found in Appendix A. Table 3.1 presents the cross-validation results using a 20-fold validation over the segmented dataset per user. Each column in Table 3.1 displays the best-chosen parameters of the basis function $M1$ and $M2$, as well as the noise e for a given percentage of the observed trajectory. These parameters were manually tuned by exploring different sets over 20-fold cross-validation to determine the optimal values over a range of parameters. The middle-colored rows in the Table 3.1 indicate the predicted cells from 1 to 15. This process allowed us to select the most suitable parameters for each percentage of the observed trajectory. So for every percentage of observed trajectory, 20 sets of different basis functions and noise were used to train the ProMP over a 20-fold cross-validation. The increments in the percentage of the observed trajectories were 5%. The training of the ProMP was cross-validated on observed percentages from 10% to 90%. The tables for these extensive results can be all found in Appendix A.

Chosen Prediction Parameters of User 1019 for Cell 15 from 10% to 90% observed trajectory

Error	0.09	0.11	0.057	0.18	0.15	0.19	0.17	0.1	0.02	0.13	0.03	0.09	0.08	0.18	0.18	0.11	0.01
M1	32	32	32	35	32	32	32	32	32	31	31	31	31	29	28	28	22
M2	20	20	20	20	20	20	18	18	18	18	18	18	18	18	18	18	18
Trajectory Prediction	10%	15%	20%	25%	30%	35%	40%	45%	50%	55%	60%	65%	70%	75%	80%	85%	90%
	9	9	8	14	9	5	9	5	9	9	9	15	10	15	14	10	15
	9	9	9	14	9	5	9	5	9	10	10	15	15	15	15	15	15
	9	13	9	14	9	9	9	5	9	10	15	15	15	15	15	15	15
	9	14	13	14	9	9	9	9	10	10	15	15	15	15	15	15	15
	9	14	14	14	9	9	9	9	10	10	15	15	15	15	15	15	15
	9	14	14	14	14	10	9	9	10	15	15	15	15	15	15	15	15
	14	15	14	14	14	14	9	9	10	15	15	15	15	15	15	15	15
	14	15	15	14	14	14	9	14	15	15	15	15	15	15	15	15	15
	15	15	15	15	14	14	9	15	15	15	15	15	15	15	15	15	15
	15	15	15	15	14	14	9	15	15	15	15	15	15	15	15	15	15
	15	15	15	15	14	15	10	15	15	15	15	15	15	15	15	15	15
	15	15	15	15	14	15	10	15	15	15	15	15	15	15	15	15	15
	15	15	15	15	15	15	14	15	15	15	15	15	15	15	15	15	15
	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
Exact Prediction	60%	70%	65%	60%	40%	50%	35%	60%	65%	75%	90%	100%	95%	100%	95%	95%	100%
Exact + Neighbour Cells	100%	95%	90%	100%	100%	90%	100%	85%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Correct Board Region	100%	95%	90%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Middle Board Region	0%	5%	10%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Incorrect Board Region	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%

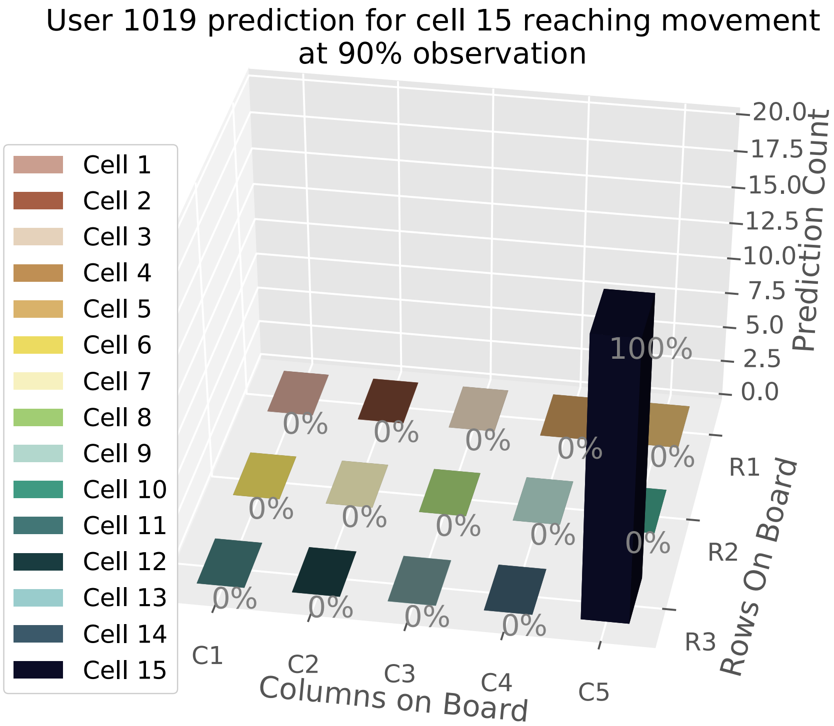
Table 3.1: Chosen ProMPs training parameters for trajectory observations from 10% to 90% for User 1019 to predict Cell 15.

Table 3.1 shows the parameters selection and the predicted cell for the 5% increments on the observed trajectory. The cells are labelled from 1 to 15 as indicated in the legend of Figure 3.29a. The bottom row of the table specifies the region to which the predicted cell is compared to the actual reaching movement target. The target cell is cell 15, located in the last column and bottom row of the cognitive board game (see Figure 3.24). The neighbouring cells to cell 15 are cells 9, 10 and 14 while cell 13 represents the cell exactly in the middle of the cognitive board game. Cell 5 is positioned above cell 10 (see Figure 3.24).

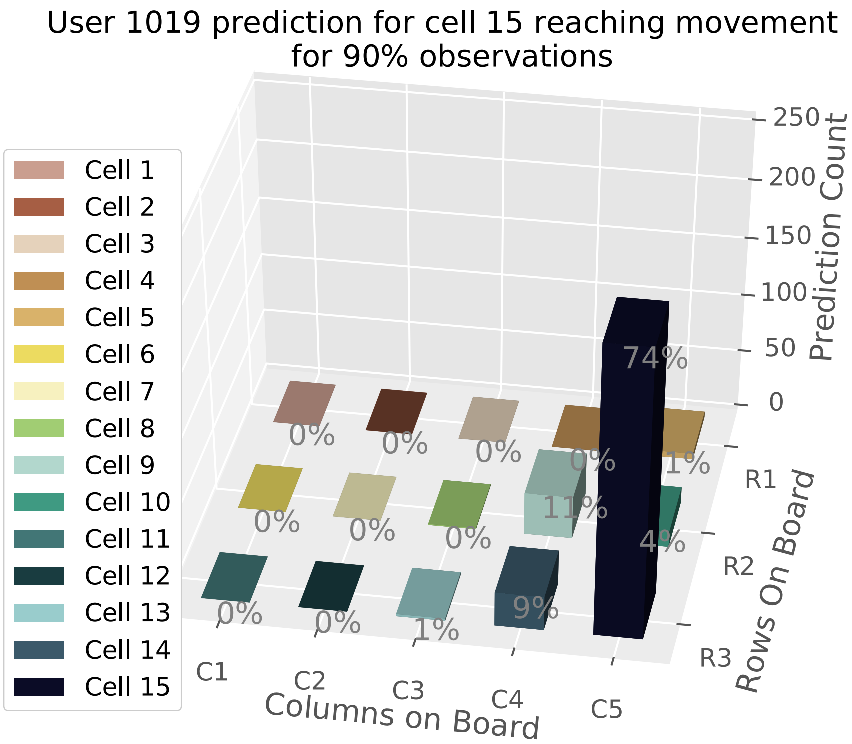
The results demonstrate that even with a very low percentage of observed trajectory, the ProMP is capable of predicting the correct region of the cell. At a 15% observed trajectory, the ProMPs predicts the target reaching movement as cell 13 once, and at a 20% observed trajectory, it predicts cell 8 once and cell 13 once. Given that each cell is an 8cm square, the corresponding error at these observed percentages is approximately 16cm. At 50% and 60% observed trajectory, the error remains within two cells above the target cell. At this point, it is worth noting that the error arises from the similarity in the movement style between cell 15 and cell 5, as cell 5 is positioned just above cell 15. For the majority of the remaining observed trajectory, it was predicted that the final reaching movement is cell 15 or the neighbour cell (cell 14 or cell 9).

Figure 3.29 shows 3D bar graphs of the predicted accuracy over the whole cognitive board game. Figure 3.29a shows the prediction for a 90% observed trajectory. The bar at 100% is the target cell on the board. From Table3.1 and from Figure 3.29a prediction at 90% observed trajectory is 100% accurate. Figure 3.29b shows the 3D bar graphs of the predicted cell locations for the grouped predicted results from 10% to 90% observed trajectory. The error of 16cm between cell 13(1% error) and cell 5(1% error) occurs at 2% out of all predicted observed trajectories. The prediction accuracy of a correct region up to 8cm of error is that of 98%. The prediction error with an 8cm prediction error, meaning that the neighbouring cell was predicted is that of 24%. The prediction of the target cell, meaning the correct location within a 8cm square, is that of 74% .

From these results, it can be seen that even within the smallest variation of 8cm as a target, there exists a methodology that can distinguish such movement and predict with high accuracy. For an overall approach it can be deduced that between 10% to 20% observed trajectory, the ProMPs can predict the correct region. Whereas, from 25% observed trajectory or higher the predicted cell will be correct within 8cm.

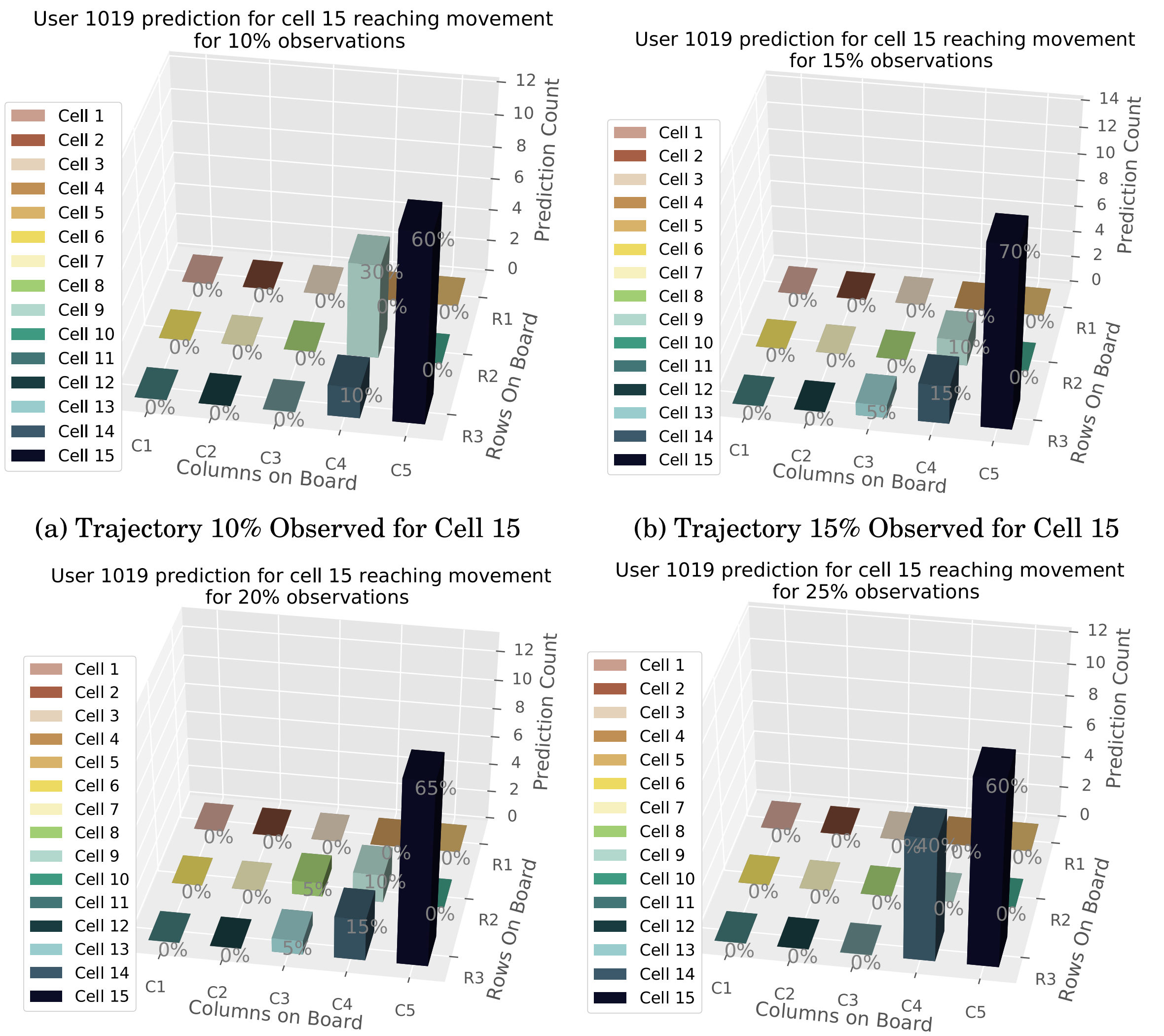


(a) Predictions for Cell 15 for trajectory observations at 90%



(b) Grouped Predictions for Cell 15 from 10% to 90% trajectory observations

Figure 3.29: Predictions for Cell 15 for trajectory observations at 90% compared to the overall grouped prediction from10% to 90%



(a) Trajectory 10% Observed for Cell 15

(b) Trajectory 15% Observed for Cell 15

(c) Trajectory 20% Observed for Cell 15

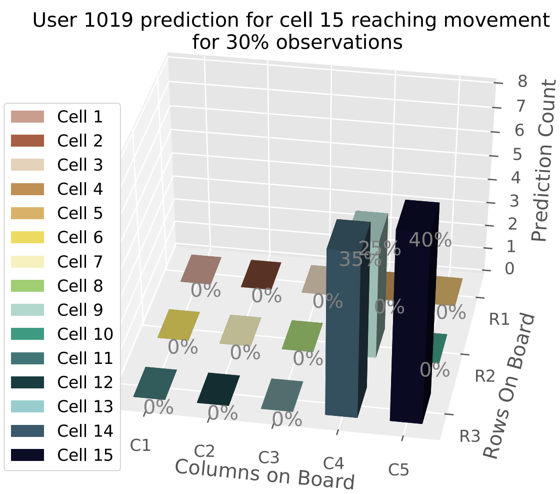
(d) Trajectory 25% Observed for Cell 15

Figure 3.30: Predictions for Cell 15 for trajectory observations from 10% to 25%

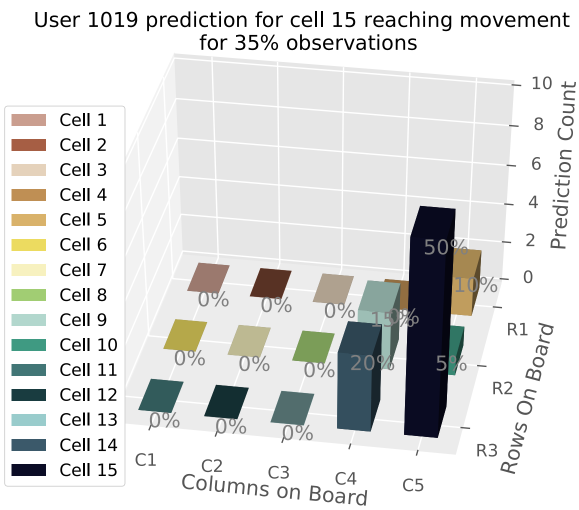
Figure 3.30 displays the 3D bar projection of the predicted cells based on 10%, 15%, 20% and 25% observed trajectory. The predictions are concentrated in the region close to cell 15, with no prediction extending beyond 5% of the total count. This level of prediction accuracy is commendable; however, it is important to prioritize physical safety. When considering a low observed percentage of the older adults' complete trajectory, the socially assistive robot should maintain a distance of at least by 16cm away from the target cell.

Figure 3.31 displays the 3D bar projection of the predicted cells based on 30%, 35%, 40% and 45% observed trajectory. The majority of predictions are concentrated in the neighbouring cells to cell 15. The prediction accuracy is slightly improved compared to the observed trajectories in Figure 3.30. Notably, there is there are predictions of 10%

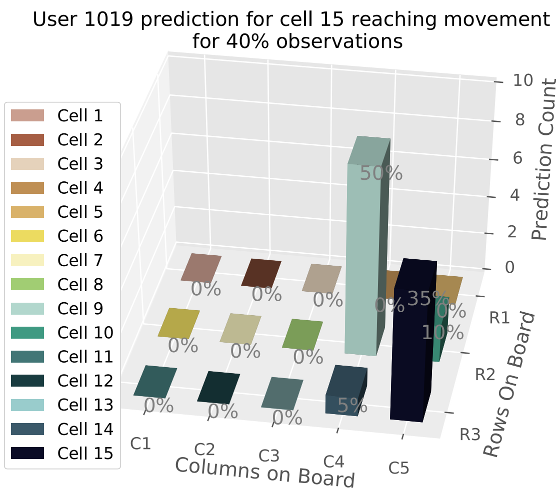
and 15% for cell 5. As previously mentioned, the trained ProMP can easily confuse these cells. The prediction is of the 35% (see Figure 3.31b) and 45% (see Figure3.31d) for the target cell 5. This confusion arises due to the similarity in y translation for the column containing cell 15, cell 10 and cell 5. Similarly, the x translation for target cell 15 can resemble that of cell 10 and cell 5 when using a low observed trajectory for prediction from a trained ProMP (see Figures 3.27 and 3.28). The same can be observed in Figure 3.31c, where the x and y translations on the cognitive board game can closely resemble cell 9. This confusion can occur when participants execute curved reaching movement directed towards the corner of the board, where column *C5* and row *R3* intersect.



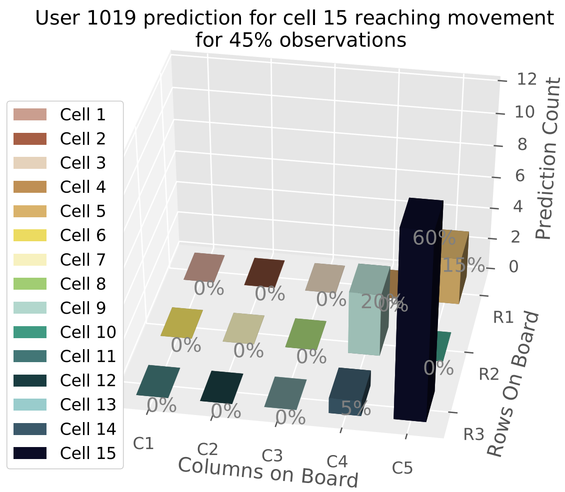
(a) Trajectory 30% Observed for Cell 15



(b) Trajectory 35% Observed for Cell 15

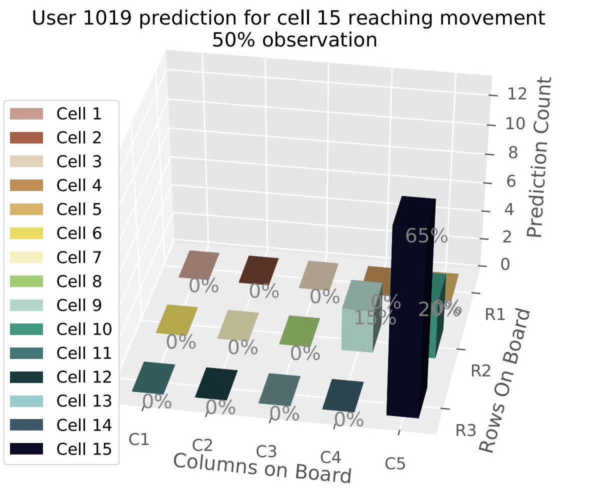


(c) Trajectory 40% Observed for Cell 15

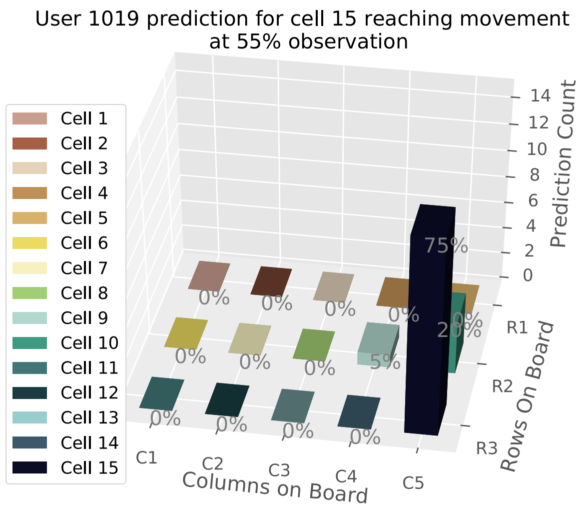


(d) Trajectory 45% Observed for Cell 15

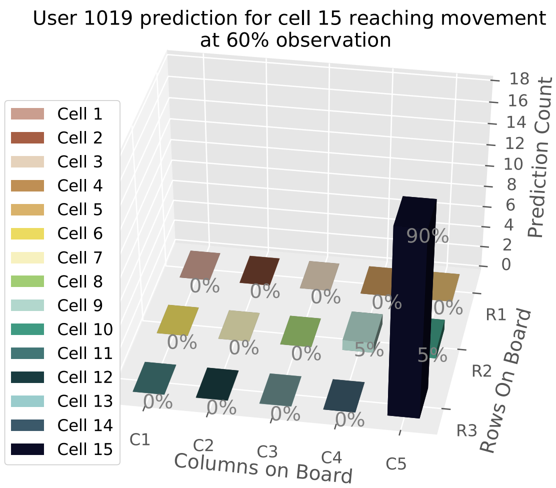
Figure 3.31: Predictions for Cell 15 for trajectory observations from 30% to 45%



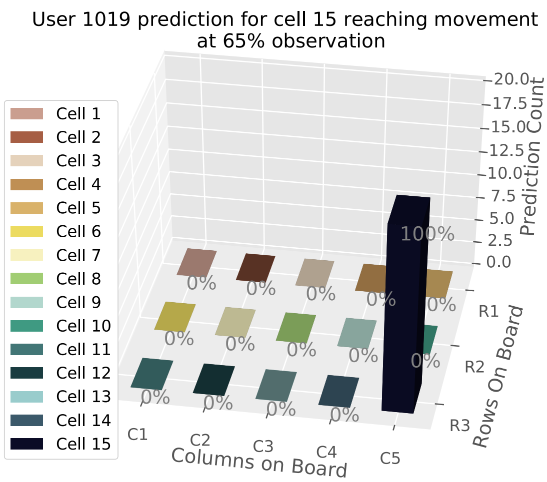
(a) Trajectory 50% Observed for Cell 15



(b) Trajectory 55% Observed for Cell 15



(c) Trajectory 60% Observed for Cell 15

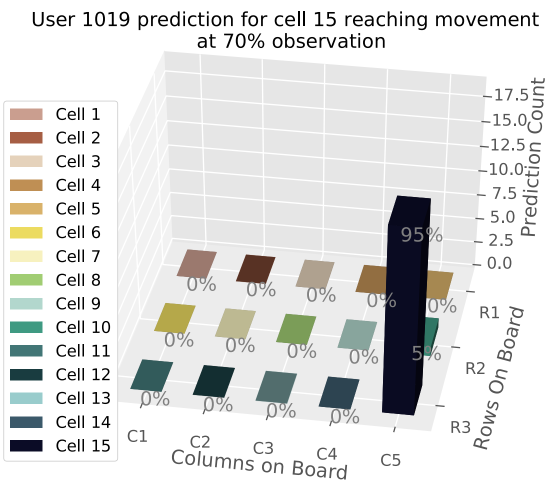


(d) Trajectory 65% Observed for Cell 15

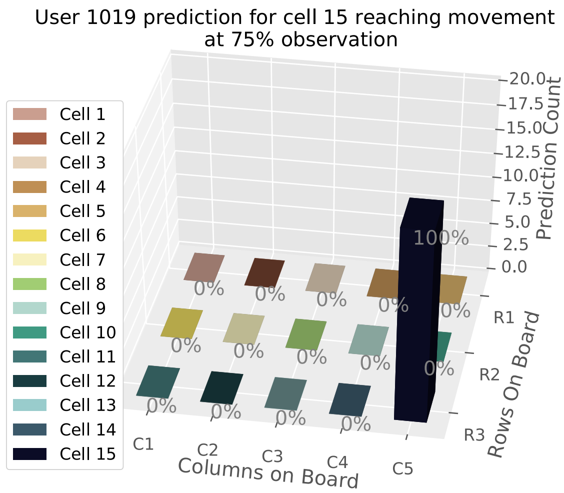
Figure 3.32: Predictions for Cell 15 for trajectory observations from 50% to 65%

Figure 3.32 displays the 3D bar projection of the predicted cells based on 50%, 55%, 60% and 65% observed trajectory. In Figures 3.32a, 3.32b and 3.32c the predictions sometimes include cell 9 and cell 10. The inaccuracy of approximately 8cm from the centre of cell 15 is due to the way human reaching movements are performed. As observed in Figure 3.11, human reaching movement tend to follow a curved trajectory. Consequently, the learned ProMPs for cell 9 and cell 10 can exhibit curved trajectories with very similar x and y translations, especially during the initially observed trajectory. As a result, the probability distributions of the ProMPs for cell 9 and cell 10 can overlap with the ProMP of cell 15.

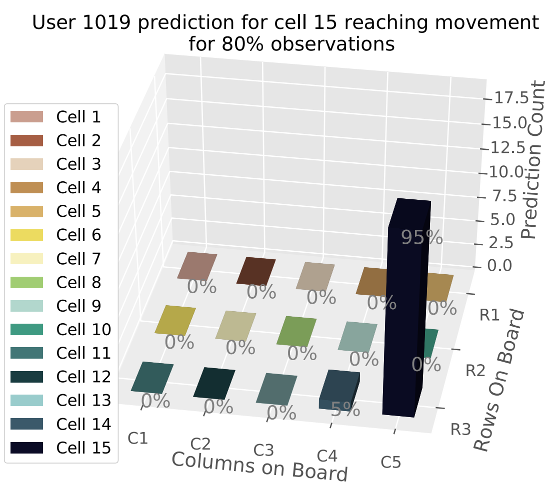
Figure 3.33 illustrates the 3D bar projection of the predicted cells based on 70%, 75%, 80% and 85% observed trajectory. The predictions in these figures are 0.95 accurate or higher. The overall result exhibited in these 3D bar projection shows that accuracy in the reaching movement prediction can be achieved up to 8 cm when observing the trajectories at 45% or more. Furthermore, It was observed that the correct region can be accurately predicted even when observing only 10% of the entire reaching movement. The correct region defines a region of 16cm away from the target cell.



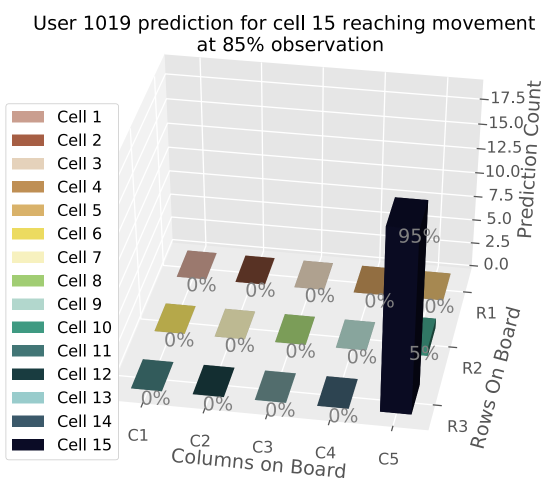
(a) Trajectory 70% Observed for Cell 15



(b) Trajectory 75% Observed for Cell 15



(c) Trajectory 80% Observed for Cell 15



(d) Trajectory 85% Observed for Cell 15

Figure 3.33: Predictions for Cell 15 for trajectory observations from 70% to 85%

3.5 General Discussion

3.5.1 Findings

The work presented in this chapter demonstrated the ability of human movement prediction to provide information to a socially assistive robot in order to maintain physical safety.

A case study CS1, was conducted to address **RQ1** and **RQ2**, which aimed to evaluate the accuracy of predicting very close human reaching movements in a real-context scenario. The results obtained from the collected dataset suggested that human movement prediction can be highly accurate when appropriate parameters are selected for the ProMPs. The trained ProMPs serve as a representation of prior knowledge about human reaching movement within the socially aHRI framework. Therefore utilizing this prior knowledge can help the robot differentiate between very close reaching targets before the human actually touches the target cell. Additionally, the results show that even slight variations in human movement can be detected, even when the reaching goal differs by as little as 8cm. When only a very little initial part of the executed trajectory is observed, this accuracy extends up to 16 cm on the cognitive game board. This means that the assistive robot can approach as close as 16cm while still observing the user in order to providing guidance and assistance in performing the cognitive game. These findings were observed to generalise across the rest of the participants. Collectively these findings strongly support **RQ1**.

On average, each trajectory consisted of approximately 50 time samples recorded by the Xsens suit at a frequency of 50Hz. This means that an observed trajectory of 10% is equivalent to around 100ms. Therefore, based on the results, it is evident that the correct region on the board can be predicted within 100ms of the older adults changing hand posture and moving toward the board. The actual target cell can be predicted within the first 450ms, allowing the robot to accurately determine the closest 8cm where the reaching movement will end. This demonstrates that within a mere 100ms, a robot can acquire knowledge about the human's intention through the modality of human movement prediction.

However, whether this time can guarantee physical safety highly depends on the context of the aHRI. In the presented case study, CS1, physical safety from the socially assistive robot can be guaranteed up to 16cm away from the human's arm reach. The physical safety in this context is required to be around the common workspace, and hence the cognitive board game. Consequently, this accuracy time window of 450ms may not be sufficient in the context of a physically assistive robot where the workspace of the robot is the human itself. All things considered, the answer to **RQ2a** is yes but answering **RQ2b** requires further analysis.

3.5.2 Lesson Learnt

This section highlights the critical lesson learned throughout the development of the prediction of human movement. Below are the most relevant ones:

- Data cleaning, preparation and sanity checks of large time-series datasets. The dataset collected from CS1 was extensive, necessitating meticulous python scripts to carefully examine and correct any inconsistencies. Properly segmenting the reaching movement trajectory and performing accurate shift checks were crucial for obtaining correct prediction results. This iterative and time-consuming process was essential to ensure reliable outcomes from real-context data. This is a fundamental requirement for the deployment of assistive robots in real-world scenarios. The same approach was also implemented when collecting data for the second case study, CS2.

- Human reaching movement in such contexts can provide added value in making aHRI more adaptive to the user needs. Being able to predict the target cell and the intention of reaching the cognitive board can enhance the sense of natural interaction. Therefore, even though other modalities may sometimes offer more intuitive knowledge to the assistive robots, input modalities need to be carefully evaluated to ensure the most successful and efficient interactions.

3.5.3 Limitations

Despite our results showing that human movement as an input modality enhance physical safety by predicting reaching movements within a socially assistive task, the current case study has specific limitations. We aim to partially address these limitations in the subsequent sections of the thesis through additional case studies and observations. These limitations primarily stem from the absence of consideration for to the lack of HF, HS and environmental factors.

- *Human Factors*: The participants selected for these experiments were all physically and cognitively healthy individuals. The time modulation of ProMP showed the ability to integrate different reaching speeds and movement styles among participants, leading to reliable prediction methodology. However, the inclusion or even the consideration of participants with diverse physical and cognitive needs was not evaluated.

- *Human State*: The participants involved in the task of performing movements for a socially assistive cognitive game were solely focused on completing the task as outlined in the provided information sheet. Their intentions were consistently directed towards task completion and collaboration was not disrupted or altered.

- *Environment Factors*: The target users of a socially assistive robot are typically older adults in care homes or home environments. This environment may introduce more distraction compared to the controlled laboratory environment in which this case study CS1 was completed.

By acknowledging these limitations, we can recognize the need for further exploration and understanding of how human factors, human state, and environmental factors influence the effectiveness of socially assistive robots.

3.6 Summary

In this chapter, we presented a methodology that could provide physical safety in a socially aHRI for individuals playing a cognitive game on a worktop table. This chapter displays the first contribution towards evaluating collaboration through human movement for complex assistive tasks.

Initially, we described the socially assistive task and the framework [9] used to adapt to the end-users needs. The framework was evaluated based on its ability to ensure physical safety by carefully assessing whether or not the physical safety could be maintained when the workspace is shared between the robot and the human. The adaption of the robot was based on the physical movement of tokens from the board game. This meant that the older adults' intentions were only known after they were actually executed.

Interaction contexts like CS1 often assume that the robot will operate at very low speeds and overlook additional physical safety requirements. One can argue that low end-effector speed and collision detection through force sensing are the only necessities for physical safety in socially assistive tasks. However, when doing so the additional benefit of having an intuitive interaction is not fully utilized, and such a claim can only stand if the interaction workspace does not become more complex. It is important to consider other factors and potential risks that may arise. The results showed that: i) human movement prediction can provide information about the intent of the human's reaching movement and therefore ensure physical safety, and ii) the accuracy of this prediction is able to differentiate between very similar movements as long as the appropriate time window is chosen to achieve the desired physical safety and accuracy on the workspace. However, the presented approach has limitations related to HF, HS and environmental factors

The remainder of the work presented in this thesis aims to tackle these limitations, Firstly, human movement will be evaluated in a more complex interaction context and assessed in a less controlled environment to mimic real- world scenarios. To properly address the observed limitations, testing the extremes of physical safety through movement prediction will be implemented by targeting to initiate a change in the human state HS as a result of environmental factors. To achieve such goals, case study CS2 (see Chapter 4) was designed to uncover factors that can hinder physical safety by influencing the success and effectiveness of a physically aHRI. Secondly, in order to ensure that human movement is evaluated in appropriate environmental factors and real contexts, observation study OS3 was carried out to access how different human factors are properly addressed by professionals in care homes when designing physically aHRI systems to meet user needs (see Chapter 5).

CHAPTER 4

Human Movement in a Physically aHRI Task - The Effects of Cognitive Overloading and Distractions

In the context of Physically aHRI close-proximity is often required, and ensuring safety and the ability for real-time adaptation are essential for achieving collaborative tasks efficiently. Safety measures, must in place for the robot to effectively avoid or adapt to dynamic obstacles, such as a human arm movement with high reliability. Additionally, the robot's adaptive behaviour in response to the human's actions is necessary to maintain synchronization and ensure smooth interaction during physically assistive tasks.

In this chapter, builds upon the findings presented in Chapter 3, where we demonstrated the ability to identify and predict variations in human movement. It was concluded that in the context of CS1, safety can be guaranteed by predicting human reaching movement on the workspace during socially aHRI. This is because the assistive task primarily involved the movement of the older adults' arm with a workspace in front of them. In physically aHRI, robots need to adapt their trajectories based on validated human movement predictions to ensure physical safety. This chapter focuses on the analysis of human movement during interaction with the Baxter Research Robot in a CPCI. The CPCI presented in the case study CS2 involves a jacket-dressing task, where the workspace is practically the human themselves. Specifically, we want to validated the input modality of human movement in the context of changing HS, HF, and environmental factors within a more complex interaction context. Therefore, human movements is examined when unexpected events occur in the surrounding environment in to evaluate cognitive and physical distraction from the physically assistive task. Our findings provide the first evidence that human arm movement have variations sometimes lead to task failures when the HF, HS and environmental factors are considered. In addition, the experimental results show that the variations in human movement are influenced by the type of unexpected events and the user's familiarity with performing and completing the assistive task. Lastly, it is observed that the variations in movement are spatially bound, meaning they occur within a certain range of movement, but they can vary temporally, leading to asynchronous movement between the human and the robot. This can result in failed synchronization of movements and unsuccessful completion of the task when unexpected events occur.

The work in this chapter is also described in the following publication:

A. Camilleri, S. Dogramadzi, and P. Caleb-Solly, ***A Study on the Effects of Cognitive Overloading and Distractions on Human Movement During Robot-Assisted Dressing***, *Frontiers in Robotics and AI* - Human Movement Understanding for Intelligent Robots and Systems, (2022).

4.1 Introduction

For robots that can provide physical assistance, maintaining synchronicity of the robot and human movement is a precursor for interaction safety. pHRIs are complex and require synchronized human-robot movements. Synchronicity for the robot involves recognizing and predicting the intentions of human movements, while for the human, it involves being ready to collaborate. Research in cognitive neuroscience, show that disruption in human movements can occur due to external disturbances, which not only affect action cognition but also motor control ([58]). Existing research on cHRI does not address how synchronicity can be affected if humans are subjected to cognitive overloading and distractions during close physical interaction.

If the robot is to safely adapt its trajectory to distracted human motion, quantitative changes in the human movement should be evaluated. To ensure safe and adaptive interactions, it is important to have prior knowledge of quantitative changes in the human movement when their behaviors is disrupted. If the behavior of the human is disrupted, then this disruption needs to be investigated further to ensure safe and timely adaptive interactions. Such prior knowledge would benefit from ensuring that any movement adaptation is implemented in a safe context and not in an instance in which the collaborative state of the human is disrupted. Understanding how a changes in behavior, caused by cognitive overloading and distractions, affects human movement in robot-assisted dressing is an important research problem that can improve pHRI and address safety concerns. Monitoring deviations from the expected trajectory and the loss of the human-robot synchronicity can provide insights on these disruptions. Previous research in similar interaction contexts, such as learning demonstration, feedback control and adaptation of robot movements [120], [49] and [87], does not consider the impact of unexpected events on human behavior, and adaptation of the robot movements assumes that the human's action cognition is solely focused on the assistive task.

In this case study, the focus is on a robot-assisted dressing using the bi-manual Baxter robot, which helps participants put on a jacket. Tracking human arms just before physical contact with the garment ensures a correct starting position for dressing. When the hand is in the sleeve, the robot trajectory can be guided by force feedback as described by [35]). However, achieving physical coupling between the sleeve opening and the human hand can be challenging before the hand enters the sleeve. At this initial stage of the dressing task, where humans can freely move their arms in a shared workspace, disruptions in human movement due to external disturbances need to be modeled for appropriate robot adaptation. While adaptation through feedback control is not possible when there is no direct physical contact [49], identifying non-collaborative instances takes priority over executing the reference dressing trajectory. Psychology literature of joint tasks shows the importance of synchronicity to achieve cooperation ([40, 140, 141]). Such literature state that poor synchronization (non-collaborative instances) between movements is perceived as an uncooperative partner, which affects the representation of the shared task. Therefore, it is crucial to understand how human motor control is affected when external disturbances occur during an assistive task.

To study the effect of the disruptions, we designed a controlled experiment to obtain reliable data and model the impact of various external disturbances. These disturbances were carefully timed unexpected events that disrupt the human movement before the hand made contact with the jacket, causing deviations from the expected trajectory. By recording the human and robot movements, we evaluated differences between the expected and disrupted human trajectory. This analysis allowed us to and quantify the disrupted human movement and model the lack of collaboration. The NASA-Task Load Index (NASA-TLI) was used to measure perceived workload and the Pertinence of Robot Decisions in JoinT Action (PeRDITA) to capture participants' perceived experience. These qualitative user experience results support the quantitative data of human movements.

Overall, this research serves as a crucial first step in addressing the challenges of maintaining synchronicity and collaboration in close pHRI when unexpected events and disruptions occur. It provides valuable insights into the impact of disruptions on human movement and highlights the importance of considering human motor control in realistic pHRI scenarios.

4.1.1 Research Questions

The main objective of this study is the analysis and quantification of disrupted human movement during a physical collaborative task that involves robot-assisted dressing. Quantifying disrupted movement is the first step in maintaining the synchronicity of the human-robot interaction. The human movement data collected from a series of experiments where participants are subjected to cognitive overloading and distractions during the human-robot interaction, are projected in a 2-D latent space that efficiently represents the high-dimensionality and non-linearity of the data. The quantitative data analysis is supported by a qualitative study of user experience, using the NASA to measure perceived workload, and the PeRDITA questionnaire to represent the human psychological state during these interactions. In addition, we present an experimental methodology to collect interaction data in this type of human-robot collaboration that provides realism, experimental rigour and high fidelity of the human-robot interaction in the scenarios. Therefore we aim to investigate the following research questions:

RQ3: In a physically assistive robot interaction context, can human behaviour impact their physical safety?

RQ3a: Can disturbances in a dynamic environment lead to unusual variations in human movement, and therefore a failed collaboration task?

RQ3b: Can prediction of human movement still guarantee safety during such known disturbances?

RQ3c: In such context, can the state-action pairing remain non-adaptive to guarantee safety during such disturbances?

RQ3d: Can some of the humans become familiar with some of the disturbances in the environment?

RQ3e: Can movement synchronization fail even though the human learned how to adapt and collaborate in the task?

RQ4: Can collaboration intent be gauged from the variations in the human movement and guarantee physically safety from a more complex state-action pairing?

4.1.2 Contributions

In addressing the above-mentioned research questions, the following contributions were made:

- Design of an experimental HRI methodology that includes timed cognitive overloading to expose changes in the collaborative interaction during a robot-assistive dressing task.

- An analysis of the changes comprising qualitative evaluation of the user experience showing how *cognitive overloading* and *distractions* increased the cognitive workload.

- The quantitative analysis of the effect of the change in collaborative behavior on human movement when exposed to unexpected events during a robot-assisted dressing task

4.2 Methodology

4.2.1 Hypotheses

In an assistive dressing task, where human movement is in close proximity to the robot, safety requires high level of confidence in predicting and adapting the robot's movement. Distractions and failures are very likely in a real-life contexts, and it is crucial to have a clear understanding of human engagement and changes in movement. From Section 2.3, it is evident that existing literature on pHRI primarily focuses on changes in human movement and overlooks human behaviors when adapting robot movement. Furthermore, the effects of distraction and cognitive overloading are rarely addressed. Therefore, in these works, select the correct anticipatory action can only be done with high confidence when there is mutual responsiveness and commitment to the collaborative task. Otherwise, the human's non-collaborative state can pose a safety risk. Based on these arguments and the ones mentioned in Section 2.3.2 understanding human cognition and mental model is necessary when instigating a lack of collaboration in interactions. There with the design of case study CS2. The aim is to evaluate the following hypotheses:

H1. User's attention from the collaborative task can be affected by cognitive overloading and distractions

H2. User's collaborative state can lead to a change in human movement.

We hypothesize that cognitively overloading humans in the robot-assisted dressing task will disrupt the synchronicity of their collaborative physical interaction. We consider how *cognitive overloading*, as well as *distractions* will unbalance the overall cognitive load made up of intrinsic, extraneous and germane loads. We also take into consideration of how the timing of unexpected events should be staged to trigger increased mental effort. Our HRI experiment explores these hypotheses by taking care of the temporal layout of these staged events (see Figure 4.1). Additionally, the nature of the unexpected staged events is based on how to disrupt the equilibrium in the mental model by looking at the different cognitive loads, which are further explained in Section 4.2.2.

4.2.2 Experiment Setup and Procedure

Our controlled HRI experiment was set up to demonstrate and study disruptions to collaboration during a robot-assisted dressing task in the presence of *cognitive overloading* and *distractions*. Our experimental procedure is shown in Figure 4.1 and Figure 4.2. We used a bi-manual Baxter research robot to perform pre-recorded dressing trajectories while a jacket was held by the gripper. The jacket was moved from the participant's hand to their elbow. Subsequently, the jacket was pulled towards the participant's left-hand side to allow them to insert their left hand/arm in the left sleeve.

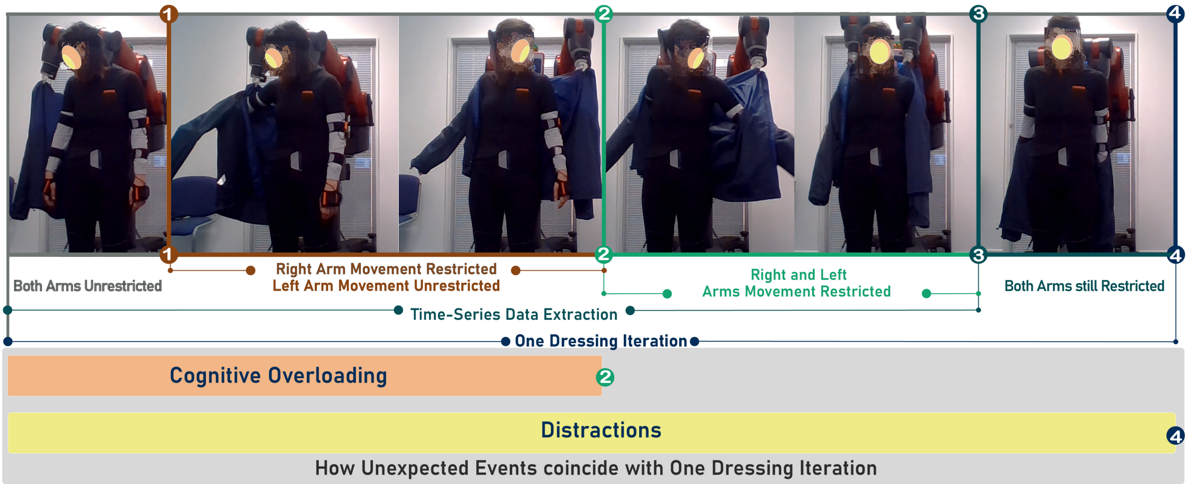


Figure 4.1: One dressing task timeline. Markers from (1) to (4) highlight the different stages during the assistive task. The first image on the far LHS shows the moment in the dressing task when the right arm is unrestricted. The following two images show the dressing with the left arm unrestricted. The two images between Markers (2) and (3) show the instance where the left hand becomes restricted, followed by an image where both hands become restricted. After Markers (3), the robot drags the jacket back down the arms of the participant. The orange block represents the time during which *cognitive overloading* occurred. The yellow block represents the time during which *distractions* occurred. For all three parts of the experiment the dressing task was repeated ten times.

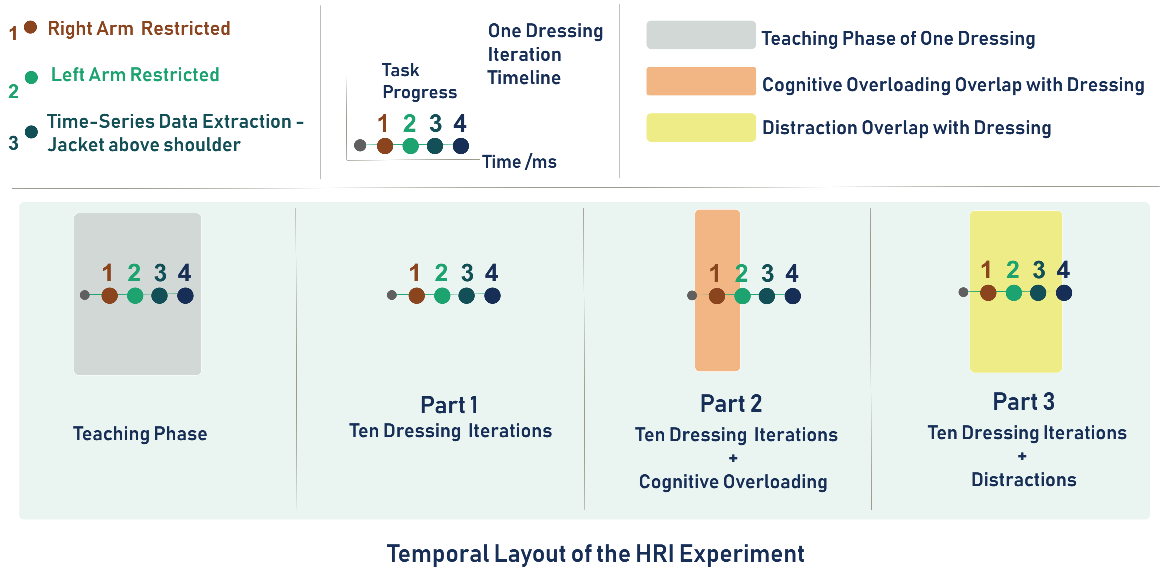


Figure 4.2: Overall experiment timeline after marker one: (i) teaching phase followed by **Part 1** made of ten dressing tasks, (ii) **Part 2** consisting of ten dressing tasks with *cognitive overloading* and (iii) **Part 3** again consisting of ten dressing tasks with *distractions*. Markers from one to four represent the same instances in the dressing task as shown in Figure 4.1.

One iteration of the dressing task is completed when the jacket reaches the participants' shoulders. The robot then pulls the jacket down and prepares for the next dressing iteration. The whole process shown in Figure 4.1 will be referred to as one dressing iteration. The researcher chose when to start the first dressing iteration.

The entire experiment is divided into three parts, with an initial learning sequence of one dressing iteration to familiarize participants with the task. The overall temporal layout of the experiment is shown in Figure 4.2. In parts *Two* and *Three*, we introduced unexpected events to disrupt human's collaborative state. In *Part Two*, the disruption to the collaborative task is the *cognitive overloading*, whereas, in *Part Three*, the disruption is in the form of environment *distractions*. A monitor was placed in front of the participants to display letters that participants had to memorize as part of the *cognitive overloading*. The letters appeared at four different positions (from the LHS to the RHS) on the monitor, and participants had to memorize four consecutive letters as they appeared (and then disappeared) from the monitor. When the fourth letter was displayed, they had to say the four letters in their order of appearance. The letters that appeared on the monitor were always different. In *Part Three* of the experiment, there were two types of distractions, one was created by sounding a fire alarm, and the other was random questioning of the participants. Each participant had two distractions that occurred during one dressing iteration, as shown in Figure 4.2. The color-coded markers, numbered one to four, in Figure 4.1 represent different sequences of one dressing task. These color-coded markers are also shown in the overall temporal layout in Figure 4.2. Marker one is a temporal mark of the jacket's initial position (participant's RHS) and when participants start inserting the right arm in the jacket's sleeve. Marker two shows when the robot positions the jacket close to the participant's left hand and when participants start inserting the left arm until it becomes constrained in the jacket. The *cognitive overloading* was applied until marker two since, at this stage, the participant's arms were still not entirely restricted by the jacket. Marker three shows when the robot end-effector reached both shoulders. At marker four, the robot starts to pull the jacket down and out of the participant's hands.

The temporal layout of these unexpected events is based on how our working memory is used to recover already learned knowledge stored in the long-term memory. In *Part One*, participants used relevant knowledge on how to collaborate in the assistive dressing task acquired in the initial learning stage. In *Part Two*, new information related to the unexpected events had to be processed, which increased their cognitive load and led to disruption in the collaborative state ([115]). *Part Two* and *Three* further imbalanced this cognitive load and disrupted the efficient storage of the new information([115]). Participants had to continuously modify their collaborative task plan based on the initially acquired knowledge of the task. To efficiently process new information in our working memory, we have to balance the cognitive load. For effective learning, the intrinsic cognitive load must be managed, extraneous cognitive load minimized, and germane cognitive load maximized. These three loads make the overall cognitive load. Intrinsic cognitive load is related to new information that needs to be processed to complete a task. The extraneous cognitive load [115] involves searching for information while trying to learn a task. The cost of processing information goes against the process of learning. Whereas, the germane cognitive load is described as an effort to construct a mental model of the task.

The Intrinsic cognitive load is often managed by good instructional sequencing, and in our controlled experiment, it is prompted by instructing participants to carry out an additional task during the collaborative dressing task. In *Part Two*, the letters appearing on the monitor were continuously changing with no obvious pattern. This increased intrinsic cognitive load due to a lack of proper instructional sequencing since it required a higher mental effort to process new information. The *distractions* in *Part Three* that included a fire alarm further increased intrinsic cognitive load. It was hypothesized that *cognitive overloading* and *distractions* would lead to inefficiency in performing the task since the intrinsic load will not be managed properly. In our experiment, extraneous loading is triggered by asking participants to remember and say the four letters in the order of appearance, marked as *cognitive overloading*. In *Part Three*, this was implemented by posing questions to the participants and triggering a new information process. These distractions introduced new tasks that prevented using the initially acquired knowledge of the collaborative task. Therefore, the extraneous load was not minimized in these instances, requiring a higher mental effort from the participants. The temporal layout of the experiment was constructed to manipulate the germane load. The unexpected events do not allow participants to use an already built mental model of the task from *Part One* therefore, the maximization of the germane load got disrupted. This overall experimental structure allowed us to analyze the change in the human's collaborative state through quantitative data collection of the human movement.

4.2.3 Human Movement Data Collection.

Participants repeated the dressing task for ten iterations in each part of the experiment, as shown in Figure 4.1. An experiment information sheet was provided before the start, explaining the dressing task and the *cognitive overloading* of *Part two*. The *distractions* used in *Part Three* were not included in the information sheet. In total, 18 participants took part in the experiment, aged 18 to 24 (4 participants) and aged 25 to 34 (14 participants). All of them had completed higher education. The experiments generated a dataset of 540 dressing tasks. The dataset includes the right and left robot end-effector poses, forces and torques, and participants' pose features. The data recorded from the robot and participants resulted in a time-series dataset with a dimension size of 753,910 by 206 features.

We recorded human movement using a motion capture XSens suit [132] to obtain 23 joint positions and orientations on the participant's body. The XSens suit provides a set of inertial measurement units that, together with bio-mechanical models and sensor fusion algorithms, can instantly validate data output. The joints recorded were the pelvis, spine, sternum, neck, head, collar bones, shoulders, elbows, hands, hips, knees, heels and toes, creating a data set of 161 features (7 readings per joint) at the frequency of 50Hz. Participants were asked to take part in the calibration of the motion capture suit before the start of each part. For the calibration process, we had to measure each participant's height, shoulder width, arm lengths, knees height, and hip height. Since this experiment focused on recording human movement disruptions, the XSens suit was used instead of RGB-D cameras to alleviate occlusion problems. The robot joint positions, orientations, forces and torques were streamed as messages in a ROS environment synchronized with the published motion capture suit data. Participants were instructed not to move their feet outside the marked area on the floor in front of them. The two joint frames of the feet were used as fixed reference frames with respect to the robot base.

From the time-series data collected, the data until marker three on Figure 4.1 were extracted from the rest of the data. This segment of one dressing iteration is represented in the first five images in Figure 4.1. The position (x, y, z) and the quaternion orientation (x, y, z, w) of the right and left arms were used for the human movement projection in a latent space. Figure 4.3 shows how one of the participants moved during one collaborative dressing task. Sub-Figure 4.3A shows the human movement recording in *Part One*. Sub-Figure 4.3B shows the human movement recording during one dressing iteration with *cognitive overloading*. There is a clear visual difference in the human movement in Sub-Figure 4.3B when compared to Sub-Figure 4.3A. The orange and green markers are the joint positions of interest to identify any disruptions in the human movement due to a change in collaborative behavior. The orange markers represent the hands, elbows, and shoulder movement, whereas the green markers represent the collar bones, head, neck, spine, pelvis, and sternum. The upper body movement was considered to analyze the type of movements and visualization on the projected latent space. The orange (shoulders, elbows and hands) and green markers (collar bones, head, neck, spine, pelvis and sternum) joint positions were used from the dataset to generate the comparison in the latent space.

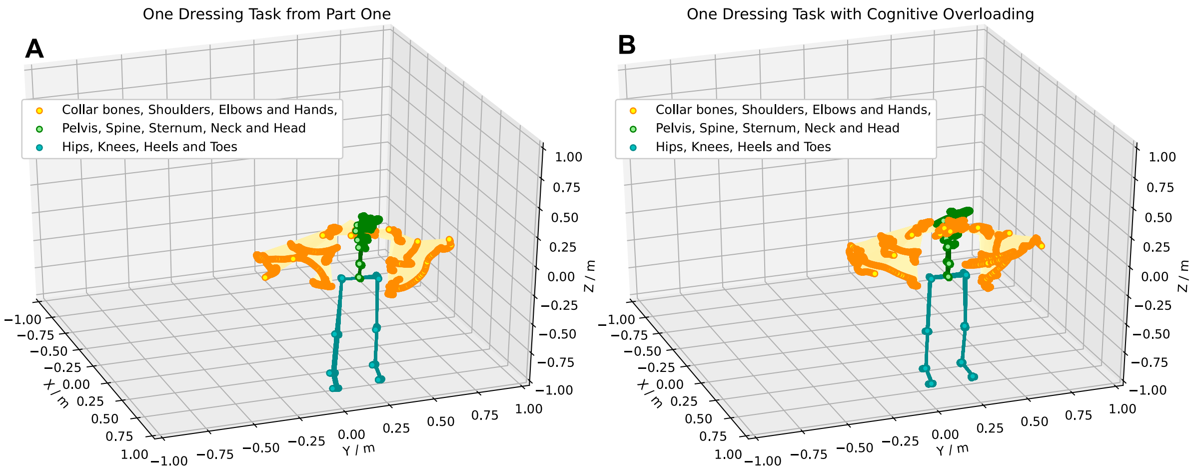


Figure 4.3: A 3D projection of the human movement recorded using the XSens motion capture suit. Sub-Figure **3A** shows the movement of one participant during one dressing iteration performed in ***Part One***. Sub-Figure **3B** shows the movement of the same participant during one dressing iteration performed in ***Part Two*** (with *cognitive overloading*).

4.2.4 User Experience Data Collection

The qualitative user experience data collection is critical for supporting our arguments based on hypothesis derived from human behavior, action cognition and motor control. We evaluated the collaborative behavior from the participant's feedback, particularly how they expressed their experience when their movement was disrupted during the collaborative task. After every ten dressing iterations, participants were asked to evaluate their workload during each collaborative task. This qualitative measure was collected using the NASA questionnaire, which was scored based on a weighted average of six sub-scales: (i) mental demand, (ii) physical demand, (iii) temporal demand, (iv) performance, (v)effort, and (vi)frustration [70]. This measure estimates the impact of *cognitive overloading* and *distractions* and verifies that participants experienced an increase in the mental effort in *Part Two* and *Three* compared to *Part One* of the experiment.

Additional participant feedback was gathered using the PeRDITA questionnaire as presented in [43]. The PeRDITA is inspired by the UX (User eXperience) model presented by [13] in which the interaction is explained in terms of:*"a consequence of a participant's internal state, the characteristics of the designed system and the context (of the environment) within which the interaction occurs."* The user's internal state includes predisposition, expectations, needs, motivation, and mood of the user, while the context of the environment includes social setting, the meaningfulness of the activity, voluntariness of use, and collaboration intention.

Dimension	Question	Items
Interaction	In your opinion, generally, the interaction was:	Negative/Positive Complicated/Simple Not practical/Practical Unpredictable/Predictable Ambiguous/Clear
Robot Perception	In your opinion, the robot is rather:	Machinelike/Humanlike Artificial/Living Inert/Animated Apathetic/Responsive Unpleasant/Pleasant Disagreeable/Agreeable Stupid/Intelligent Incompetent/Competent
Collaboration	In your opinion, the collaboration with the robot to perform the task was:	Restrictive/Adaptive Useless/Useful Unsettling/Satisfactory Annoying/Acceptable Insecure/Secure
Verbal	In your opinion, robot verbal interventions were:	Incomprehensible/Clear Insufficient/Sufficient Superfluous/Pertinent
Acting	In your opinion, the robot actions were:	Inappropriate/Appropriate Useless/Useful Unpredictable/Predictable

Table 4.1: PeRDITA Questionnaire: Questions describing each dimension. Items are evaluated in a scale of 100

The PeRDITA questionnaire assesses several aspects of interaction as shown in Table 4.1 which form part of the five dimensions of interaction. The *Interaction* dimension quantifies the participants' behavioral intention, and this dimension is based on the AttrakDiff questionnaire proposed by [91]. The *Robot Perception* dimension evaluates how participants perceive the robot and is based on the Godspeed questionnaire as presented in [13]. The other dimensions provide insights into how participants perceive joint actions in the robot assistive task and include the *Acting, Verbal* and *Collaboration* dimensions. *Acting* is a measure of the human perception of the decisions taken by the robot. *Collaboration* quantifies the cooperation with the robot in terms of acceptability, usability, and security. No *verbal* communication is used in this experiment. During dressing, people do not tend to use clear verbal communication and instruction can be ambiguous as shown in [34].

4.3 Results

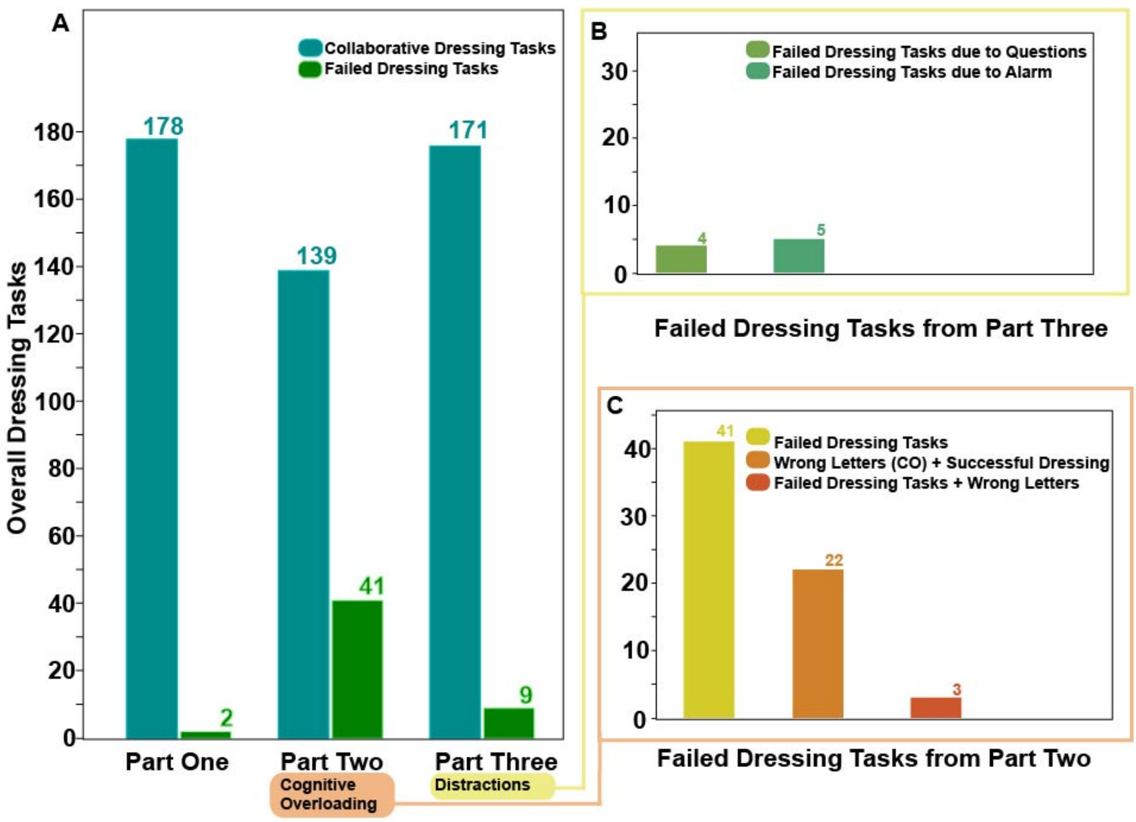


Figure 4.4: Dressing failure and mistakes count in the different parts of the HRI experiment. Sub-figure **A** shows the dressing failure in **Part One**. Sub-figure **B** shows the dressing failures that occurred in ***Part Three***. Sub-figure **C** shows the dressing failures and mistakes that occurred during the *cognitive overloading* in **Part Two**.

Figure 4.4 shows a breakdown of the dressing failures and mistakes during the 180 dressing iterations for each part of the experiment. In *Part One*, we recorded two failed dressing iterations. In *Part Two*, there were 41 failed dressing iterations, whereas in *Part Three* there were nine dressing failures. In addition to the dressing failures in *Part Two* some participants failed to memorize the four consecutive letters appearing (and disappearing) from the monitor correctly. This means that a total of 22 mistakes occurred during the rest of the 139 collaborative dressing iterations in *Part Two*. Three out of the 41 dressing iterations were both mistakes in recalling the letters as well as dressing failures. From the failures that occurred in *Part three*, five were attributed to the fire alarm and four to the random questioning. The term dressing failure means that participants missed the opportunity to synchronize their movement with that of the robot to enable the insertion of the right arm or left arm in the jacket. This suggests that the *cognitive overloading* might have hindered the participant's ability to adapt and collaborate with the robot.

4.3.1 Evaluation of User Experience and Work Load

As described in Section 4.2, the qualitative data collection aims to understand the participants' experiences of the disruptions in collaboration during the dressing task. Participants were asked to answer the PeRDITA questionnaire, explained in Table 4.1 by marking from 0 to 100 each item in the dimensions of the interaction. The PeRDITA questionnaire aims in getting feedback about how participants perceive their collaboration with the robot during the dressing task. The PeRDITA results obtained from our controlled HRI experiment is shown in Figure 4.5 and Figure 4.6.

Sub-figure 4.5A shows the box-plots for the dimension of the interaction of *Acting*. Participants were asked to rate the interaction in terms of appropriateness, usefulness and predictability. Overall, the participants describe the collaborative task as *useful, predictable* and *appropriate*. The score of the item *Predictable* in the *Acting* Dimension of Interaction suggests that participants perceived the robot's trajectory to be predictable in the context of the collaborative task. Such a score was recorded even though the participants failed to maintain a collaboration behavior during unexpected events. Sub-figure 4.5B shows the box-plots for the *Robot Perception* dimension. The Baxter Research robot was described as *machine-like* instead of *human-like* and *artificial* instead of *living*. An average score between 50 and 60 was given to the items of *animated, responsive* and *pleasant*. The majority of the 18 participants described the robot as *agreeable* and *competent*.

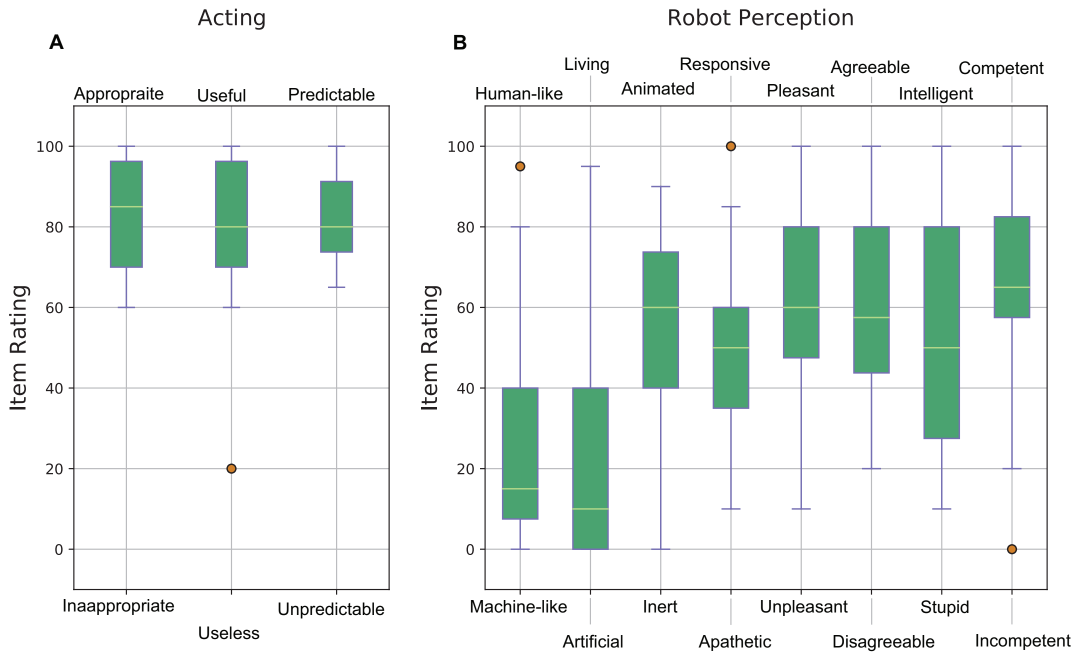


Figure 4.5: Results of the PeRDITA questionnaire for the *Acting* and *Robot Perception* dimensions. Sub-figure **A** shows the item ratings forming part of the *Acting* dimension, and sub-figure **B** shows the item ratings for the *Robot Perception* dimension.

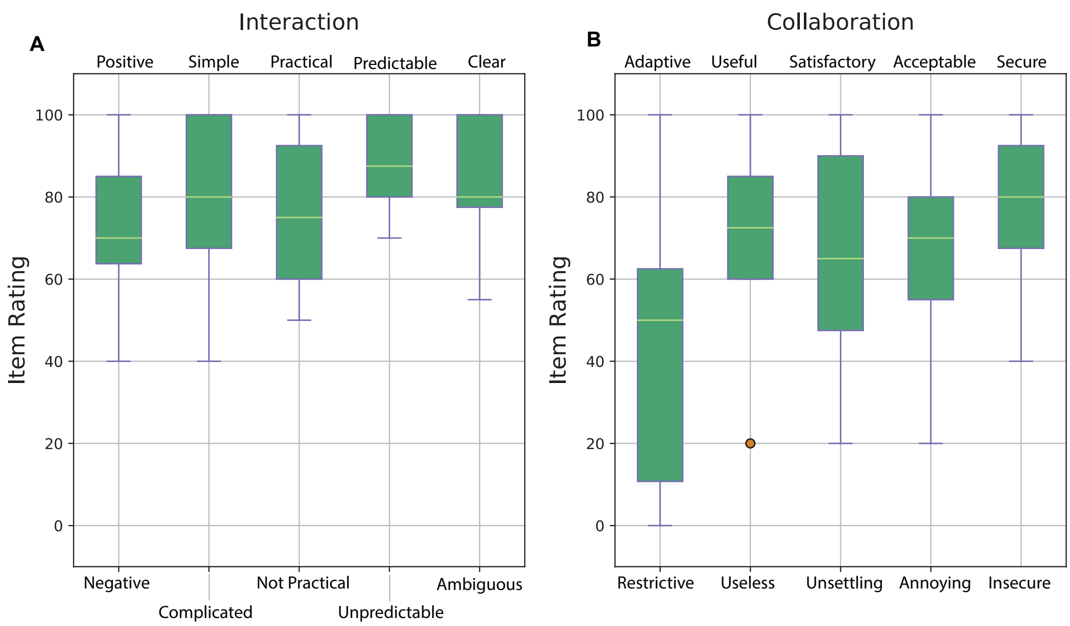


Figure 4.6: Results of the PeRDITA questionnaire for the *Interaction* and *Collaboration* dimensions. Sub-figure **A** shows the item ratings forming part of the *Interaction* dimension, and sub-figure **B** shows the item ratings for the *Collaboration* dimension.

On the other hand, the item of *intelligence* during the collaborative task had the largest variance from all items. A few participants did perceive the robot as *human-like*, *responsive* and *not competent*. The robot was classified as appropriate to carry out the collaborative task even though the robot did not adapt to the participants' changing behavior.

Figure 4.6 shows results from the rating of the *Interaction* and *Collaboration* dimensions of interaction. Overall, the *Interaction* dimension results shown in sub-figure 4.6A is described as *positive, simple, practical, predictable* and *clear*. Although the verbal dimension was non-existent in the experiment, the interaction dimension achieved a high score. This suggests that verbal interaction was not considered as important in being able to achieve this physically assistive interaction. The trajectory executed by the robot was implemented in such a way as to mimic humans helping each other to get dressed. The participant's ratings of the *Collaboration* dimension are shown in sub-figure 4.6B. The collaboration dimensions in the controlled HRI experiment were highly regarded as *secure, acceptable,* and *useful*. A lower average and higher variance are recorded in the *Satisfactory/Unsettling* item. This significant variance might be due to the mistakes and dressing failures during the collaborative task. An even higher variance and a lower average are seen in the *Adaptive/Restrictive* item. These low ratings can be attributed to the lack of adaptation from the robot side. The uncertainty in participants' ratings could be attributed to the fact that they might think they have failed in collaboration due to unexpected events. The highest rating in the *Adaptive* item is from one of the participants who did not have any dressing failures in *Part Two*. The participants who did not let the *cognitive overloading* affect their collaborative behavior might have gotten the impression that the overall collaboration was more adaptive. As such, these participants might perceive the robot as more *adaptive* when compared to the other participants' experience. The lowest rating of the *Adaptive* item is given by the participants who failed both the dressing task and gave the wrong answers to the *cognitive overloading* task. Hence, the variance in rating the *Adaptive* item in the PeRDITA questionnaire could be linked to the varied effect of the *cognitive overloading* on different participants. It is essential to note that the PeRDITA questionnaire was evaluated after Part One, Two and Three were finished. We can only argue that these results are an overall evaluation that includes the cases with no cognitive overloading and distractions. Any observation of these items can indirectly be an effect of the cognitive overloading or distraction because these were still part of the overall interaction. Still, a direct conclusion cannot be made with respect to the individual parts of the experiment.

In order to evaluate the participant's perceived mental effort during the different parts of the controlled HRI experiment, the NASA was used. After ten dressing tasks, meaning after each part of the experiment, the participants were asked to evaluate their mental, physical, temporal demand, effort, frustration, and performance in collaborating with the robot for the assistive dressing task. Figures 4.7 shows the results obtained from participants after performing ten dressing iterations in *Part One* of the experiment compared to the task load demanded during *Part Two* of the experiment. Figure 4.8 shows the participants perceived load during *Part Three* compared to load perceived during *Part Two* of the controlled HRI experiment.

Overall, participants described *Part Two* of the controlled HRI experiment as the highest in terms of workload, particularly in mental, temporal demand and effort in executing the collaborative task. Initially, participants struggled to balance their attention between collaborating to perform the physically assistive task and the *cognitive overloading*. This cognitive overload caused the participants to focus less on when and how to move to maintain a collaborative behavior with the robot. The occurrences of the failures and mistakes in *Part Two* suggest that when participants could not manage the intrinsic cognitive load, they seem to prioritize either the collaborative tasks or memorize the letters on the monitor. The controlled HRI experiment in *Part Two* required participants to balance their attention between the temporal requirements of the unexpected events and the collaborative task. The only two participants who managed to carry out *Part Two* of the experiment without dressing failures gave the most wrong answers in comparison with all the other participants, indicating that their priority was on the dressing task. Furthermore, the highest measure of frustration is observed among the participants with the highest combined dressing failures and wrong answers count. The participants who both made errors in the dressing task and gave a wrong answer at different instances were also the ones who rated the temporal demand the highest. In *Part Three*, the distractions reduced control over the intrinsic cognitive load and caused participants to deviate from the plan of performing the assistive task.

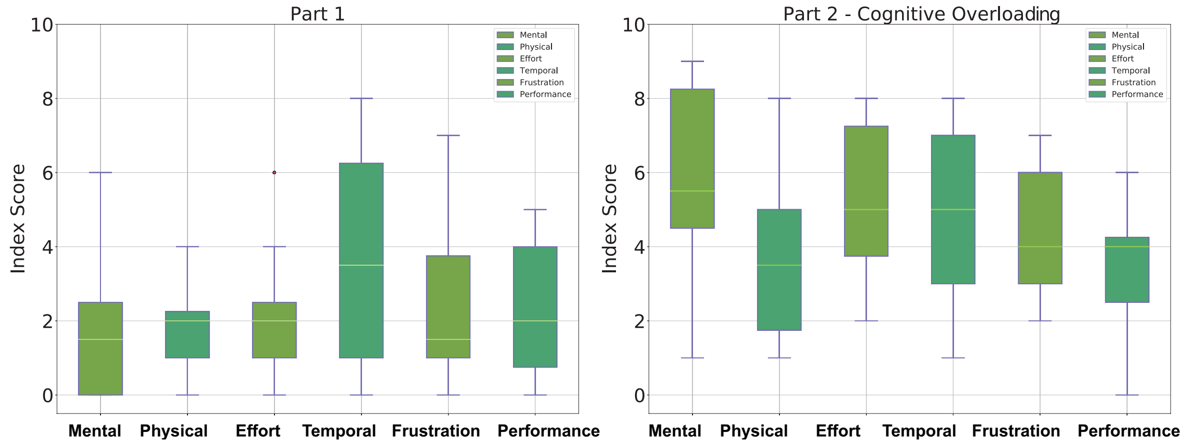


Figure 4.7: Box-plots showing the NASA TLX data collection from participants. Sub-figure **A** shows the workload in *Part One* compared to sub-figure **B** which represents the increased workload due to *cognitive distractions*.

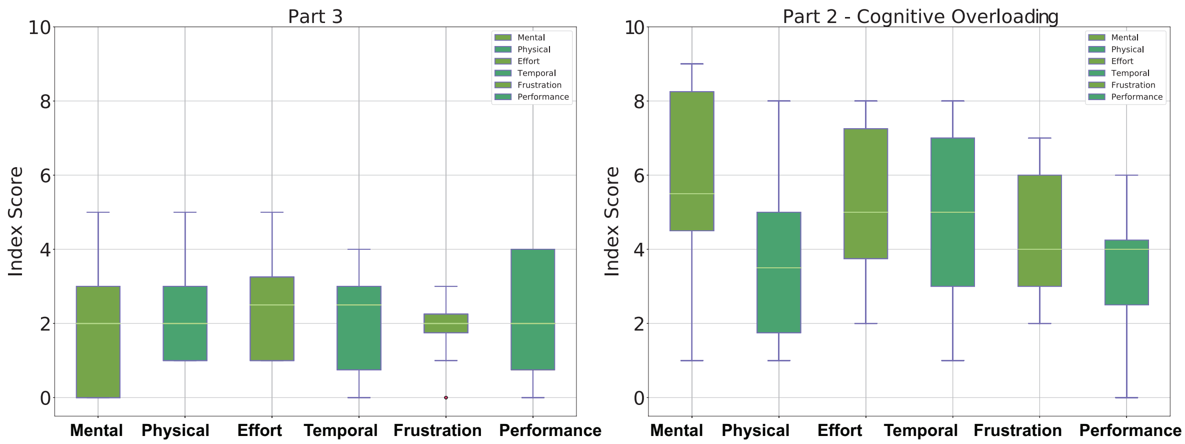


Figure 4.8: Box-plots showing the NASA TLX data collection from participants. Sub-figure**A** shows the workload in *Part Three* compared to sub-figure **B** which shows the workload from participants during from *Part Two*.

The overall increase in the workload described by participants from the NASA supports our hypotheses for the design of the controlled HRI experiment. The results suggest that controlling the occurrence of the *cognitive overloading* and *distractions* during the collaborative task managed to trigger the unbalancing in the cognitive loads. The general overview of these results shows that no matter how familiar the participants were with the task, the *cognitive overloading* and *distractions* in *Part Two* and *Part Three* caused disruption to the participants' movements. Therefore, this controlled experiment shows that in spite of an already known interaction, unexpected events may lead to variations in the performance of experienced users interacting with a robot, ending with non-collaborative partners. Such disruptions in human movement will be critical in collaborations that require synchronicity. Consequently, this highlights the importance of analysing and evaluating the changes in human collaborative behaviors and human movement, particularly during assistive tasks.

4.3.2 Evaluation of Collaborative Human Movement Disruptions

Through the controlled HRI experiments we were able to evaluate the effect of action cognition on motor control to assess how the change in the human collaborative state disrupts the human movement under *cognitive overloading* and *distractions*. As shown in Figure 4.3, there is a clear difference in disrupted human movement between the different parts of the experiment. From each part of the experiment, the movement of both arm poses was extracted from the recorded data. The data points are the joints marked as collar bones, shoulders, elbows and hands in Figure 4.3. Overall, 753,910 arm poses have been recorded from a total of 23 joints from the entire human posture. Each joint comprises seven features (position and orientation) as described in Section 4.2.3.

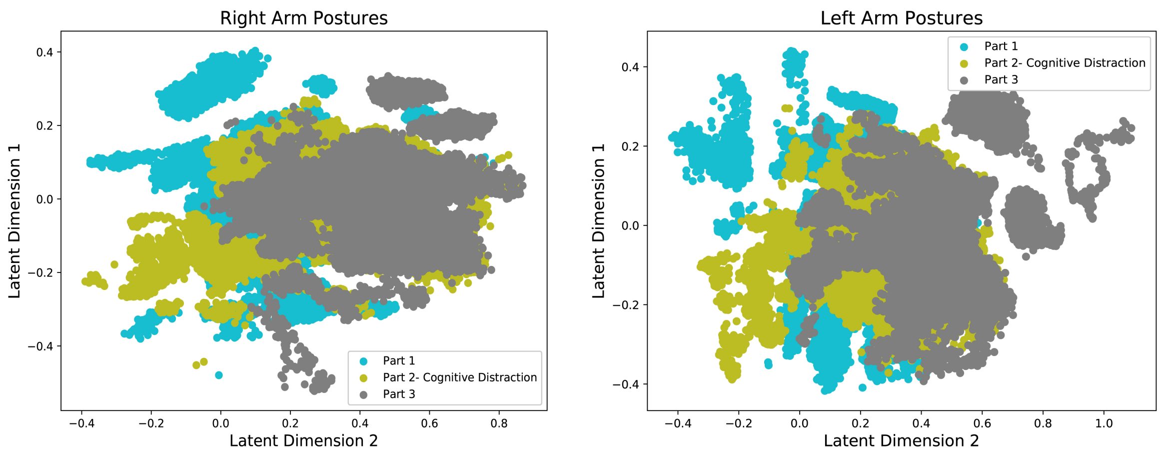


Figure 4.9: The 2-D latent space representation of the 9-D right and left arm posture data **for all participants**, produced with GP-LVM. The different colored projections denote arm movements during cognitive overload.

The human arm movement data were projected into a 2-D latent space using the GP-LVM [57]. The 2-D latent space reveals differences in human movements between different parts of the experiment. Figure 4.9 shows a map of the right and left arm poses in 2D space with three sub-spaces in different colors, indicating three different parts of the experiment. Figures 4.10 and 4.11 show right and left arm latent space, respectively, for each part of the experiment (sub-figures A, B and C). The latent spaced projection for ten individual participants can be seen in sub-figures D, E and F of Figures 4.10 and 4.11. From *Part Two* in Figures, 4.10 and 4.11, the variation in the right arm movement is greater than the variation in the left arm movement. During this part of the experiment, the *cognitive overloading* was overwhelming the participants because they could not process the information presented to them while also simultaneously participating in the assistive task.

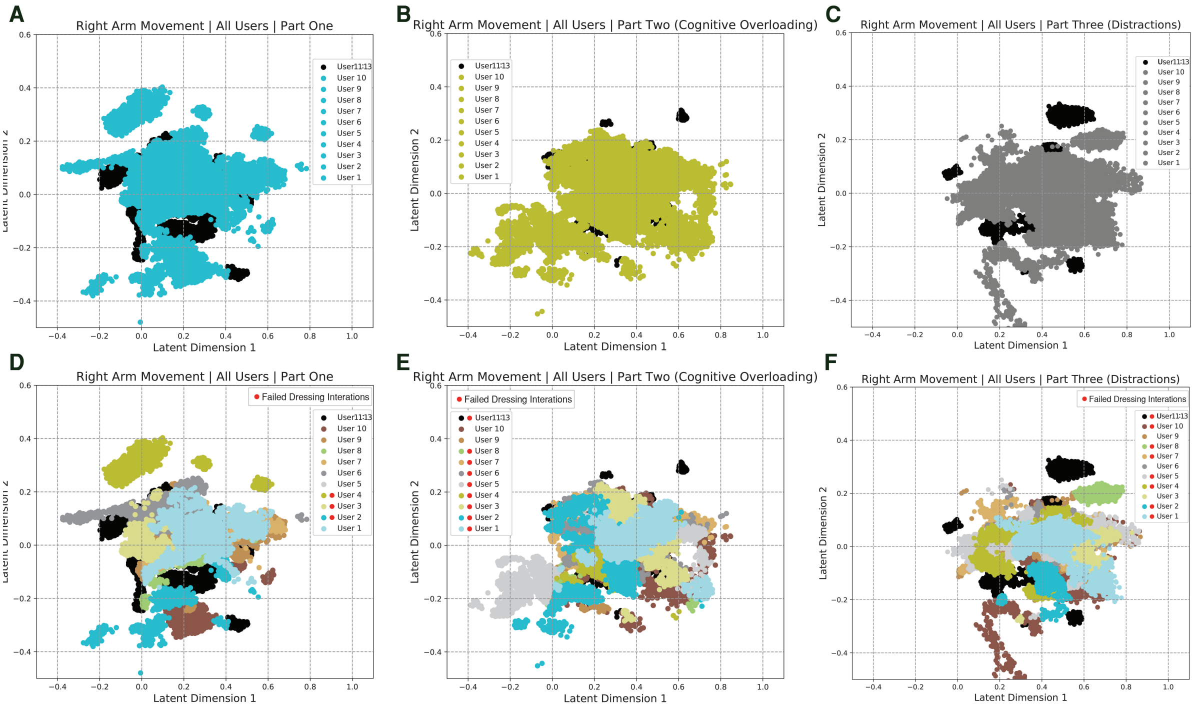


Figure 4.10: Separated Latent Space representation of the right arm movements for Part One **(A,D)**, Part Two **(B,E)** and Part Three **(C,F)**. Sub-Figures **A,B,C** show the 2-D latent space representation for all the participants. Sub-figures **D,E,F** shows the representation of ten individual participants. The participants marked with a red dot in the legend had dressing failures in their dressing iterations.

It was observed that during the initial part of the dressing task (until marker two in Figure 4.1), participants got agitated by quickly trying to move the right arm first but failing to synchronize their movement as they did in *Part One*. It was observed that participants who failed to insert the right arm in the jacket gave up trying to insert the left arm in the jacket, hence the fewer variations in the latent space. The overall representation of the projection indicates that participants used similar movements, somewhat restricted to a particular subspace shown in the central part of the graphs.

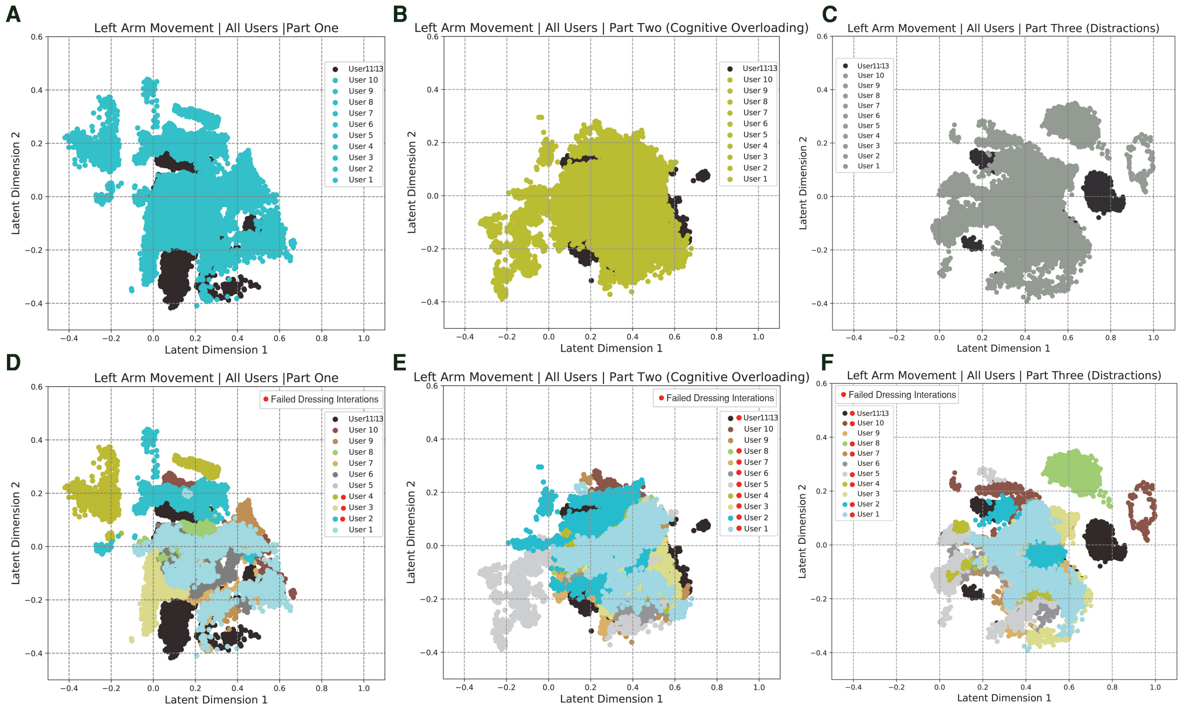


Figure 4.11: Separated Latent Space representation of the left arm movements for Part One **(A,D)**, Part Two **(B,E)** and Part Three **(C,F)**. Sub-Figures **A,B,C** show the 2-D latent space representation for all the participants. Sub-figures **D,E,F** shows the representation of ten individual participants. The participants marked with a red dot in the legend had dressing failures in their dressing iterations.

This subspace can be assumed to show fundamental arm poses during collaborative behavior. Figure 4.12 shows density distribution of the projected latent space from Figure 4.9. The lighter colors represent higher densities of human movement during the whole experiment. Figure 4.12 shows how the majority of the movement is centered on the latent space, meaning that most of the movement during the assistive task was consistent. Figure 4.4 shows that overall the success count of collaborative tasks was higher than the failed dressing task. This higher success rate suggests that a higher density can be attributed to a collaborative region rather than the non-collaborative states. Hence the lower density range areas on Figure 4.12 should be the regions where a significant difference between Part One, Two and Three should be observed, as seen in Figure 4.10.

A timeline of latent space changes is shown in Figure 4.13, demonstrating variations in the right arm movement during all three parts of the experiment. The latent space is divided into quadrants for ease of analysis and comparison of the different parts of the experiment. The first column shows the latent space projection of the *Part One* of the experiment. There is a broader distribution at the first iterations of the controlled HRI experiment. At this stage, participants were starting to learn how to collaborate and build a plan for the collaborative task with the robot. In the second and third columns, the distribution of the projected points is less spread because over time, presumably as the participants were able to learn the task and so undertake it in a more controlled and automated learned manner. However, this automated or learned motion is disrupted by *cognitive overloading* in *Part Two* depicted by projections in column two. The main difference from the projected movement in column one is the top right corner. The projected movement in this quadrant is associated with the timestamp when dressing failures occurred during the collaborative task. In column three, the same can be seen in all the top right quadrants. Additionally, there is a variation in the bottom row of column three compared to columns two and one. These outliers in the latent space in *Part Three* are related to the nature of the unexpected events. For example, the fire alarm sound caused some participants to move away from the collaborative task; the random questioning provoked some participants to stop collaborating and move back to the starting position. These type of movements are relatively different from the ones shown in columns one and two.

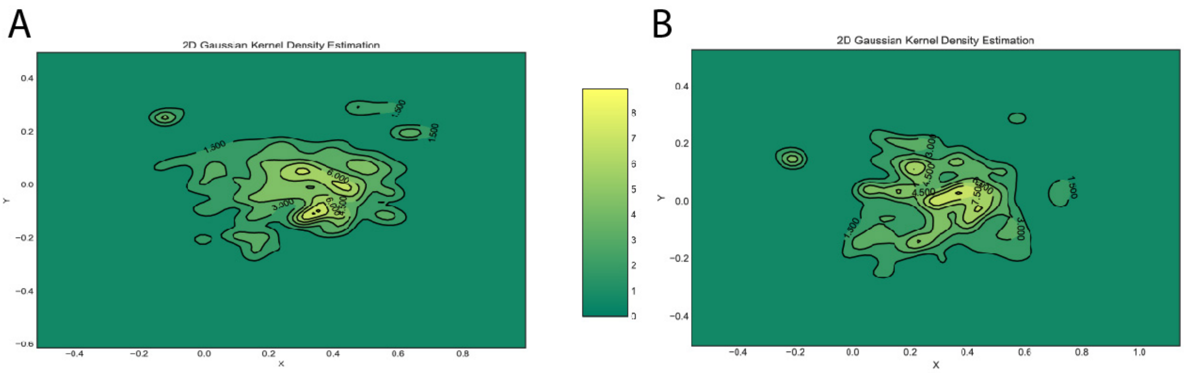


Figure 4.12: Plot of the probability distribution function using a Gaussian 2D KDE. Sub-figure **A** shows the density surface for the right arm of the participants. Sub-figure **B** shows the density surface for the left arm of the participants. Figure changed to 2D plot with color gradient instead of 3D.

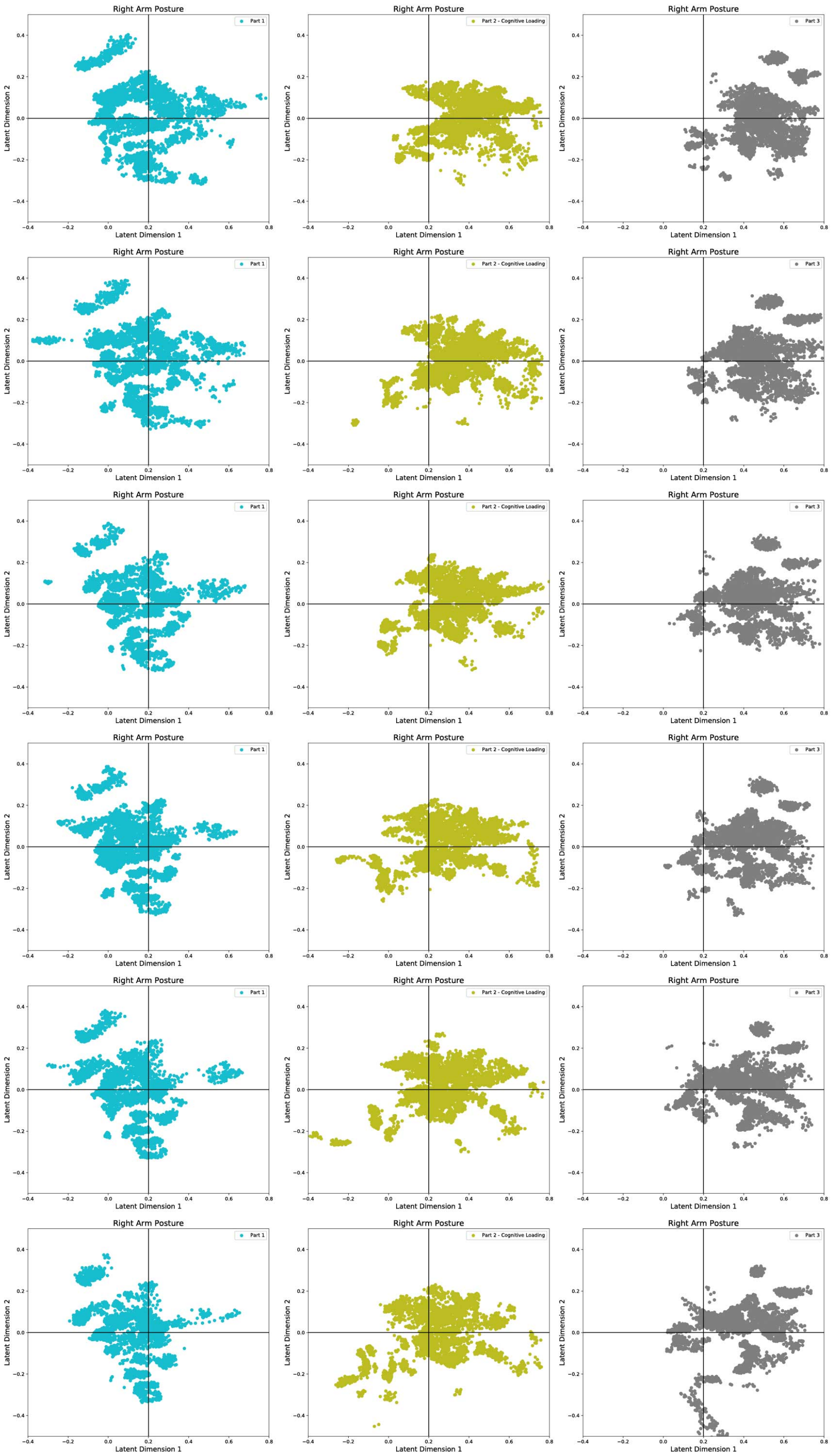


Figure 4.13: Comparison of latent space projections during different parts of the experiments along the progression in the dressing sequence. The progression of *Part One* is represented by the LHS column, *Part Two* by middle columns and *Part Three* by the RHS column.

4.4 General Discussion

The main goal of the work presented in this chapter was to evaluate whether and to what extent environmental factors can affect the human behaviour (HF and HS) and how these factors can impact the input modality of human movement in physically aHRI that requires CPCI.

4.4.1 Findings

In literature related to close-proximity robot-assistive tasks, consistent human movement during physical collaboration is always assumed. This assumption of a continuous commitment to the collaborative task from the human side can pose a safety risk in a real dynamic environment. The case-study presented in this chapter is an important step towards recognizing and characterizing the breakdown in collaborations that can occur during cognitive overloading and distractions while performing assistive tasks.The main contribution of CS2 is the analysis and quantification of disrupted human movements during a physical HRI task. The effects of the disruptions were further confirmed through the qualitative evaluation of the user experience. The timeline (see Figure 4.1) and temporal layout (see Figure 4.2) of the HRI experiment devised for this study are based on the literature on human behavior, action cognition and motor control. Consequently, these frameworks can serve as valuable resources for other researchers conducting similar studies aiming to induce cognitive overloading in collaborative tasks. Results collected through the NASA and PeRDITA questionnaire further help validate the HRI experiment's methodology. The dressing failures, mistakes (see Figure 4.4), and the qualitative feedback from the participants were found to correspond to the quantitative human motion data. These results address **RQ3a:**, since the dynamic nature caused by cognitive overloading and distractions leads to unusual variations in human movement. These variations in human movement ultimately result in failed dressing tasks.

Parts Two and *Three* of the experiment were specifically designed to disrupt the way participants initially learned to perform the collaborative task. The results shown in Figures 4.7 and 4.8 suggest that the *cognitive overloading* in *Part Two* can lead to unmanageable intrinsic cognitive load and large extrinsic cognitive loads. In *Part Three* of the experiment, the recorded data shows slightly less movement than in *Part Two* which demonstrates that participants managed the new information in the environment slightly better than the first time (in *Part Two*). The participants learned how to collaborate in *Part One*, but the unexpected events continuously challenged the germane load during the experiment. The NASA TLX (see Figure 4.7) for *Part One* shows a higher temporal demand than *Part Three*. The difference is most likely associated with the fact that during these initial ten iterations of the experiment participants were still trying to understand the dynamics of the collaboration, and build their own approach to performing the task. The breakdown of collaborative behavior is also represented in the PeRDITA results. Although participants overall described the **Interaction** as *simple, predictable* and *clear*, there was uncertainty in describing the **Collaboration** as *adaptive*. The participants collaborating with the robot, particularly in the *Part Two*, had the impression that they failed to adapt - they learned to carry out the task in *Part One* but failed to maintain synchronicity during *cognitive overloading*. All participants either made a mistake or a dressing failure during the *cognitive overloading*. The participants who did not fail in the dressing task answered most questions incorrectly during the *cognitive overloading*. These findings directly answer **RQ3d** as they demonstrate that some participants were able to become familiar with the assistive task despite the cognitive distraction. However, it is important to note that even though participants may become familiar with the task, it cannot be guaranteed that new distractions will not cause failed tasks again, emphasizing the ongoing potential for safety risks in physically aHRI. Furthermore, the results also confirm that even when participants were familiar with the task, they still lost concentration when unexpected events occurred, leading to a loss of interaction synchronicity. These findings directly answer **RQ3e**, as they indicate that even though participants had time to familiarized with the assistive task, humans still failed to adapt and collaborate in *Part Two* and *Part Three*. The successfully completion of tasks in *Part One* shows that movement synchronization was present, but it can no longer be guaranteed if the HS is affected when environmental factor. These results validate both hypotheses **H1** and **H2**. The collaborative task was significantly affected, primarily due to variations in human movement that led to a loss of synchronization between the human and the robot, resulting in a non-collaborative state.

The failures and mistakes in *Part Two* and *Three* were caused by the changes in the human's collaborative state. The projection of the human movement on the latent space shows the learning process across all three parts of the experiment. Despite minimal dressing failures in *Part One*, there is a greater dispersion of points in the latent space, indicating that participants were still learning how to execute the task. The germane cognitive load, which involves constructing a mental model of the task was likely high in *Part One* as participants were still building their mental model. This learning process is reflected in the high variance of the temporal effort from the NASA (see Figure 4.7).

The high temporal effort indicates that participants were learning how to synchronize their movements with the robot. The projections for *Part Two* and *Part Three* show that disrupted movements moved away from the center of the 2D latent space, which was not the case with non-disrupted movements. The projections show that when the cognitive loads are unbalanced (as in *Part Two* and *Three*), the ability to retrieve the knowledge of how to perform the task is affected, impacting human motor control. The projected 2-D latent space captures movements performed during the learning phase, movements performed in synchronicity with the robot, and movements disrupted due to unexpected events. To answer **RQ3b**, the findings in this chapter indicate that participants' cognitive load can be easily affected. Therefore, approaches like CPCI and prediction methodologies observed in literature cannot assume physical safety when their prior knowledge only includes optimal behavior of human movement. The findings emphasize that human movement cannot always be assumed to be fully willing to collaborate, suggesting that the answer to **RQ3b** is no. Such arguments also echo and verify the answer that was give to **RQ2b**, in Chapters 3, that human movement prediction cannot guarantee enough physical safety unless knowledge about the cognitive load of the participants is monitored.

In context like CS2, the projections on the 2D latent space suggest that a more complex stat-action pairing needs to be used to guarantee physically safety. This means that some projection on the 2d latent space represented the human movement during the collaborative state of the participants, while others did not. These findings indicate that the answer to **RQ3c** is no, and to guarantee safety this latent space of human movement needs to be mapped to robot action desired when the human is not in the collaborative state. Conducting research to evaluate assistive robots in these context prior to the deployment will strengthen assistive robots by providing prior knowledge about what human movement is intended for collaboration and what human movement is not intended for collaboration. These evaluation can be done using 2D latent spaces if a proper latent spaces analyses can show differences between the different parts in the experiment. Therefore these argument partially address **RQ4**. Furthermore, Chapter 6 extends the answer to this research question by exploring ways of creating complex state-action paring that can measure collaboration through the modality of human movement.

Additionally, the collaborative state of each participant requires some form of personalization. By looking at the user experience and mistakes presented in Section 4.3, it is evident that every participant can react entirely differently to external disturbances.

The impact of cognitive overloading and distraction on human motor control is distinctive due to its complex form. Therefore the collaborative and non-collaborative state of the assistive robot would still require some form of personalization to cater for these differences based on the specific end-user. The need of personalization exposed in this chapter is also reiterate and emphasized by the caring professional in the next Chapter 5.

4.4.2 Lessons learnt

The results presented in this chapter highlight the importance of considering the mental model that end-users will have in aHRI. The following key lessons can be drawn from the fact that the human state is affected:

- Human movement cannot always be solely based on prior knowledge that only considers the optimal behavior of humans. If fully autonomous assistive robots are to be deployed, physical safety cannot be guaranteed without using experimental methodologies similar to the one applied in CS2 for testing.
- Human movement, as an input modality, has the potential to provide insights about the human state if the dataset includes the knowledge that CS2 provided. This can offer a unique solution, especially considering that some older adults might not be able to use other input modalities.
- The qualitative data from participants clearly demonstrate that environmental and external factors impact the attention of humans when interacting in assistive tasks that require some form of collaboration between the robot and the human.

4.5 Summary

In this chapter, we presented a physically aHRI case study to evaluate a more complex interaction and what it entails to maintain physical safety through the evaluation of human movement as an input modality. Firstly, the temporal design of the experiment revolved around the research question and the hypothesis made. It was crucial to demonstrate a change in the human state, as the hypothesis stated that this would lead to task failures and therefore put physical safety at risk. The temporal layout of the experiment helped create this context. The changes in the human state were planned through the use of cognitive overloading and distractions while the participants carried out the physically aHRI task of jacket dressing. Results showed that: i) Participants experienced difficulty in successfully completing the collaborative task when cognitive overloading and distractions were introduced into their environment during the assistive task. This suggests that these factors had a negative impact on their ability to collaborate effectively with the robot; ii) Participants reported a higher perceived task load when distractions and cognitive overloading were present during Part Two and Part Three of the experiment. This indicates that these factors increased the cognitive demands and mental effort required from the participants to perform the task; iii) Despite the potential for learning and familiarization with the collaborative task, the findings suggest that it cannot be guaranteed that the collaboration intent of the users will never be disrupted in such a complex assistive task. This implies that even with prior experience and knowledge of the task, external factors can still interfere with the collaborative state and lead to failures in task execution. and finally iv) The study demonstrated that failed collaboration in physically assistive tasks can be examined and understood through a proper evaluation of human movement. The data collected on human movement in the case study revealed that an increase in participants' cognitive loads resulted in variations in their movement patterns. These variations were reflected in the 2D latent space extracted from the human movement data.

By analyzing the patterns and dispersion of human movement in the latent space, it becomes possible to gain insights into the impact of cognitive loads on collaboration. The variations observed in movement patterns can provide valuable information about the disruptions and challenges faced by participants during the task. This analysis helps to uncover the relationship between cognitive load, human movement, and the collaborative state. Therefore, by evaluating and analyzing human movement data, researchers can gain a deeper understanding of the dynamics of collaboration in physically assistive tasks. This knowledge can inform the design of future systems and interventions aimed at improving collaboration and ensuring physical safety in human-robot interactions. The limitation in the work presented here is that the analysis and projection on the 2D latent spaces required a more extensive analysis to extract specific differences between the different parts of the experiment. Additional, CS2 exposed some major challenges when it comes to providing physically assistance.

Therefore, the remaining work presented in this thesis aims to address these limitations. The primary objective is to investigate how the challenges identified in the CS2 case study can be addressed in the context of an actual care home. This exploration involves evaluating how assistive tasks are approached from a safety perspective and how hazards are assessed by caring professionals. This investigation leads to the formulation of the OS3 research question and is discussed in detail in Chapter 5.

Furthermore, the thesis aims to leverage the experience and expertise of caring professionals in order to analyze the dataset acquired from CS2. By incorporating their approaches and insights, a safety measure or methodology can be developed. This approach acknowledges the valuable knowledge and practices that professionals adapt during assistive tasks and seeks to integrate these findings into the analysis of the CS2 dataset.

By combining insights from the care home context, evaluating safety considerations, and leveraging professional expertise, the thesis aims to contribute to the development of effective safety measures and methodologies in the field of physically assistive robotics through the contributions made in Chapter 6.

CHAPTER 5

A Study with Professional Carers on Physical Safety for Physically aHRI in Care Homes.

Physical assistance to humans by humans is integral in environments such as care homes and hospitals. The tasks carried out are elaborate and successfully adapted to the different needs of assisted adults in uncontrolled environments, making such interactions highly complex. As seen in the previous chapters, the interaction requirements in terms of task complexity and safety for physically aHRI (see Chapter 4) increase extensively compared to socially aHRI (see Chapter 3). Therefore, it is necessary to understand how professional caregivers provide this assistance.

This chapter presents the third case study in the form of an observation study **OS3**, to uncover insights directly from professional caregivers and understand their interaction style, cues and guidelines used to execute assistive tasks. In other words, we pose the *what-if* questions to professional caregivers. Undeniably, this knowledge is essential to identify gaps in hazard analysis and define interaction and hardware design standards in aHRI.

OS3 utilizes a focus group methodology, allowing for an inductive analysis to generate models of the functional and non-functional characteristics that assistive robots will require. These findings contribute to the development and assurance of assistive robots by highlighting a detailed set of issues and concerns that impact user acceptance, but also safety and should thus be considered when designing such technology. These issues and concerns represent the *unseen data* and hazards that robotics researchers often overlook. While there are existing hazard analysis and risk assessment methodologies for robot safety, these standard approaches fail to address the complexities and uncertainties involved in the interaction and its environments. Physical assistive tasks in a care scenario often require direct contact with the user and require a multi-modal perception of the situation and the user. This close proximity interaction demands a comprehensive hazard model that takes into account the issues arising from interacting with a frail or ill end-user. This observation study focuses on identifying the shortcomings in the current standard methodologies when investigating physical assistive tasks. The findings provide a more precise overview of the formulation of metrics derived from these requirements. Metrics-oriented case studies are crucial for developing and designing future approaches and standards in pHRI, in conjunction with further studies and literature in this field.

Aspects raised by carers indicate that irrespective of the degree of vulnerability of the older adults, carers can evaluate trust and the older adults' ability and willingness to collaborate by multiple modalities. The carers' ability to access this guarantees safe, ethical, viable and dignified assistance. These modalities include tactile, visual and verbal cues, which the carers use to determine the level of collaboration and adapt their assistance accordingly. Understanding these shortcomings in terms of hazards directly influences the design of assistive robots. Conversely, understanding the modalities of interaction used for effective collaboration is vital for developing a safe interaction and addressing the problems and limitations uncovered in **CS1** and **CS2** (see Chapter 3 and 4).

Parts of this chapter are presented in the publication:

A. Camilleri, S. Dogramadzi, and P. Caleb-Solly, **Learning from Carers to inform the Design of Safe Physically Assistive Robots - Insights from a Focus Group Study**, in Proceedings of the *2022 ACM/IEEE International Conference on Human-Robot Interaction*, Sapporo, Hokkaido, Japan, 2022, IEEE Press,p. 703-707.

5.1 Introduction

The growing research in assistive robotics reflects the increasing staff nursing/care shortage and rising costs of daily assistance [130]. Nearly 80% of the residents in care homes need some form of assisted living support [106]. Despite significant research in this area, there is still much to be done to ensure the safety and effective interaction required for deploying these technologies in care homes.

Physically assistive procedures, such as sit-to-stand or dressing, are successful because carers can perform complex motion control using feedback from the environment and making informed decisions based on tactile and visual cues and verbal communication. These modalities, combined with knowledge about the patient's physical and cognitive conditions, dictate the decision-making process regarding when to start, stop, or modify an assistive task. Carers continuously assess the situation and adapt their assistance to keep patients safe, relying on their intuition and reasoning from various modalities to match the patient's ability to collaborate. Before addressing these issues, researchers need to analyse these interactions and precisely define the tasks and frailty levels of technologies so assistive robots, can realistically and ethically address them.

Previous work evaluating the hazards in assistive tasks has highlighted the limited research in real-world contexts (see chapter 2), leading to the inability to apply traditional hazard identification methods in these settings. Standards and regulations literature [25] also emphasise the need for assistive robots to support personal autonomy, which requires an accurate user model to maintain safe collaboration. Additionally, both [25] and [69] question the ability of physically assistive robots to interact and collaborate when changes occur in the physical and cognitive abilities of older adults, which results in added complexities. Literature on socially assistive robots [149], emphasizes the importance of measures to gauge the interaction. However, most physically assistive robot technologies lack adequate detail in experimental and clinical evaluations, suggesting the need for new measures[149]. This knowledge gap in assistive robots materialises the need to evaluate the interaction in a care home context and validate it from the point of view of healthcare professionals and end-users. In work presented in [160], focus groups are used to inform to design and use of a robot in a socially assistive context. Measuring trust [92], acceptance [127], and persuasion [161] are all aspects aimed at validating HRI by ensuring effectiveness, suitability and safety. Furthermore, there is an increase in the use of learning actions to control assistive robots [98]. However, for physically assistive robots in real-world contexts, these actions can only be deemed adequate, suitable and safe when all the hazards in every interaction context are considered. Otherwise, like the Challenger tragedy and as exposed in Chapter 3 and Chapter 4 we are imposing the wrong questions.

5.1.1 Research Questions

Based on evidence from the literature, the main goal of the work presented in this chapter is to expose the real requirements that carers impose to deliver safe and efficient physically assistive tasks. Within the breadth of this chapter, the aim is to address the following research questions:

RQ5a: How do carers physically assist older people in order to guarantee physical safety?

RQ5b: What do carers think that the requirements and guidelines for physically assistive tools or robots should be?

RQ5c: Do carers think physical safety can be guaranteed by only looking at the optimal behaviour of humans?

5.1.2 Contributions

In addressing the above-mentioned research questions, the following contributions are made:

- The presentation of opinions of professional carers on how they use various interaction modalities to acquire, maintain, and provide safe assistive tasks while aware of the safety hazards in the surrounding context.
- A comparison of safety hazard analysis with respect to the requirements specified by the professional carers.

These insights from professionals show that robotics researchers need to go beyond understanding the actual hazards experienced during a physically assistive task and derive a suitable measure/type of collaboration to fulfil the needs of the person being assisted. After accessing these hazards, we highlight the modalities care professionals use to identify hazards and what actions they take to ensure that collaboration is maintained.

5.2 Methods

Safety standards and procedures have been recognised and accepted for many years in well-established safety-critical systems industry sectors, such as transportation (automotive and aviation) and infrastructure. However, in emerging fields such as aHRI, the field still lacks appropriate methodologies and standards for safety design and assurance while considering the operational complexities of these applications. Most of the (international) safety regulations for robotics published to date have been for the industrial environment, where a robot is restricted from operating behind barriers (e.g. in a cage) with no physical contact present during the procedure. Such regulations cannot apply to physical assistance robots, which involve close pxHRI. In these applications, direct contact with users in a home environment is essential to achieve the goal of the assistive task. Therefore, regulations that require physical barriers are no longer appropriate.

pHRI is being addressed through industrial robotics standards such as ISO TS 15066:2016. The latter provides regulation for some collaborative operations in manufacturing tasks. For service robotics, standard ISO 13482:2014 has been introduced as a first-generation standard specifying safety requirements and guidelines for robots in "personal care" (however, that term is defined in a general sense and not intended to include healthcare, social care or medical care tasks). Hence in both cases, these standards are lacking in consideration of contextual issues for health/social care domains, including the vulnerability of the end-user. There is still a lack of procedures, operating rules or significant bench-marking for the environment on how these assistive robots are required to operate compared to an industrial environment.

When the requirements vary depending on the cognitive, physical and sensory ability or impairments of the end-users, it can be even more challenging to identify hazards correctly. Additionally, assistive robot interaction needs to abide by clinical regulations and guidelines from a safety perspective. Dangerous situations and risks to the end-users well-being are highly likely due to their lack of experience with technology or robot interactions. Although the communication between the end-user and robot can be a valuable modality for completing the task, it can be inconsistent and variable, resulting in an additional level of uncertainty. Therefore, having an effective safety-critical assistive solution requires taking into account the user preferences for predictive and safe human-robot interaction and the uncertainties in the surrounding environment that affect human behaviour and robot performance.

Nursing and care staff are the individuals that have the necessary experience and knowledge in making assistive tasks safe, identifying hazards and encouraging people to collaborate and interact to their best ability while achieving the assistive task. Understanding the users and environment, in which these assistive robots operate provides an invaluable contribution to the safety and hazard identification process. They can help identify the appropriate requirements which can lead to establishing metrics that help to achieve repeatable and consistent performance and aid in evaluating using pHRI methodologies. This chapter intends to expand the existing literature concerning safety standards and metrics in pHRI. Additionally, it aims to provide insights into forming new safety guidelines for physical assistive robots, drawing from the perspectives of professionals well-versed in assistive care. Traditional hazard identification methods will be utilized to identify hazards in physically assistive tasks. These identified hazards will then be compared with those identified by nursing and care staff, emphasizing the need to reevaluate metrics in assistive pHRI. Furthermore, we access such metrics and how these can be applied to human movement in aHRI and expand on the results from Chapter 4 CS2 to the ones presented in Chapter 6.

5.2.1 Safety Analysis Processes

The most widely used safety analysis techniques are Failure Mode, Effects and Criticality Analysis (FMECA), functional hazard analysis (which includes Hazard Operability Analysis (HAZOP), Preliminary Hazard Analysis (PHA) and software-oriented techniques such as Software Hazard Analysis and Resolution in Design (SHARD)[122], and Fault Tree Analysis (FTA). Systems Theoretic Hazard Analysis (STPA) is a relatively new technique and is still not widely practised in industry, although its popularity appears to be growing [5]. Safety analysis processes are usually performed as an adjunct to the general system development process, typically in the following order:

1. Preliminary hazard analysis is applied at the very earliest stages of requirements analysis, to capture the key hazards associated with the essential functional requirements of the system. PHA is often performed by review of the early functional requirements in natural language, with minimal use or availability of the models that are available in subsequent development stages.

2. Functional hazard analysis techniques (for example, HAZOP, SHARD, Functional Hazard Assessment (FHA) [44, 64, 159]) are generally applied to a system model (specification), to achieve a systematic and exhaustive identification of potentially

hazardous functional failures. HAZOP is now a standard by [44], and it considers possible alternatives to the main parameters of the procedure.

3. FTA and FMECA are usually used at the detailed design stage rather than requirements specification and are aimed at developing causal models showing how internal faults or errors may contribute to the occurrence of a functional hazard. These techniques are not usually considered to be hazard identification or analysis methods unless by chance a system-level hazard is revealed as the cause or consequence of an internal failure, which had been missed in earlier stages of safety assessment.

5.2.2 Overview of Hazard Analysis Methods

A number of variations of hazard analysis methods exist. The following paragraphs provide an overview of some of the most widely used methods, as well as some that are novel or have features of interest to this chapter.

5.2.2.1 Aviation Sector FHA

FHA as practised in the aerospace sector and codified in the ARP 4761 standard [1], was one of the earliest variants of this class of analysis to come into use. FHA identifies three generic types of functional hazard (dysfunctional mode):

- Failure to operate as/when intended
- Unintended or inadvertent operation
- Malfunction (a.k.a. misleading function)

The method proceeds by positing each of these three hazard types against each functional requirement of the system. Hypothetical conditions that are implausible can be ignored, but for all others, a precise description of the failure condition is defined. Then, for each failure condition, the consequences of the condition are identified. Since the nature of the system's environment often varies throughout the operational use of a system, the consequences are assessed over different partitions of the system mission (in an aircraft these are its flight phases such as take-off, landing, cruise, etc.) in order to identify different consequences of the same failure condition if it was to occur in different environmental circumstances. The severity of the harm of each distinct consequence is determined, usually in terms of the number and degree of injuries caused to persons (crew, passengers or third parties). These hazard identification results are then used as the basis of a risk assessment, where the severity assessment of each potential hazard is used to determine a design target for the rate/probability of its occurrence, as specified by aviation industry standards and regulations. Additional regulations also specify further safety requirements as a function of the severity level, particularly for fault tolerance within the system architecture design. The results of the FHA are usually presented in a tabular format.

5.2.2.2 HAZard and OPerability Studies HAZOP

This method, originally developed in the chemical process control industry, has become one of the most widely known hazard analysis methods. The official reference is the IEC 61882 standard [51]. HAZOP proceeds by a systematic analysis of failure conditions in the flow parameters across the boundary interface of the system. In general, flows are any information (data, signals), energy (electrical or mechanical power), fluid flow (chemical reagents, fuel), or mechanical force (structural loads and stresses, mechanical actions) that pass across the system boundary.

HAZOP identifies a number of *guide-words* which have the same role as the generic failure conditions of Aviation FHA. Guide-words are generally tailored to the technological domain of the system being analysed, i.e. different keyword sets for electrical/hydraulic/pneumatic/mechanical machines, fluid dynamical interfaces or mechanisms, analogue or digital electronics, or software. However, the general concept of guide-words is that they relate to *flows* of energy, force, information, or physical material across the system boundary interface, and generally identify *deviations* in the value, timing, or provision those flows. The guide-words that were originally identified for the original HAZOP version and are specified in IEC 61882 [51].

The method proceeds by developing an interpretation table for the flow parameters of the system, where the guide-words are applied to the parameter types present in the system, and specific definitions of the failure conditions are defined (if the combination is plausible). Then the relevant interpretations are applied to the actual parameters of the boundary interface and the effects on system functions and consequences on its interaction with the environment are assessed. The results are tabulated in a similar manner to Aviation FHA.

5.2.2.3 Software Hazard Analysis and Resolution in Design (SHARD)

Since HAZOP was originally developed for industrial process control systems, variants of HAZOP have been proposed for computer systems and software, which follow the same general methodology but propose guide-words that are more appropriate for flows of data and electronic signals than fluid and mechanical forces. Two variants of note are defined in the UK Defence Standard 00-58 and the SHARDmethod, developed at the University of York [122] is notable in that it proposes a different set of guide-words developed from a survey of computer/software failure cases. The new guide-words are related to the functional service that is provided through a given flow parameter:

i *Service provision failures*

- *Omission*: Functional service not provided when intended
- *Commission*: Functional service provided when not intended

ii *Service timing failures*

- *Early* : Functional service provided earlier than intended
- *Late*: Functional service provided later than intended

iii *Service value failures*

- *Coarse Error*: Value of input parameters to the functional service is coarsely incorrect (illegal value)
- *Subtle Error*: Value of input parameters to the functional service is subtly incorrect (value is legal but incorrect)

The SHARD guide-word set was derived from earlier studies and surveys of real incidents of computer-related failures [122].

5.2.2.4 System-Theoretic Process Analysis (STPA)

STPA comprises a more comprehensive analysis of the development process, while also considering potentially unsafe behaviours. In [20], verifies that the STPA method can provide better results than standard hazard assessments because it allows multi-interaction expansion in the early stage of development, but also includes alternative interaction states. STPA has been implemented on autonomous vehicles changing lane action in [3] with improved analyses because it could tackle and generate various types of interaction requirements. Correspondingly, in [17] STPA is applied to an autonomous multi-robot system inferring that the capability of taking into consideration a more extensive set of potential scenarios can make it a more effective hazard analysis technique because unsafe and unintended interaction can be accounted for.

5.2.3 Issues of Model Dependency, Sufficiency and Completeness in Functional Hazard Analysis

The goal of many functional hazard analysis exercises is to be as *systematic* and *complete* in the process of identifying hazards as is reasonably practicable. The rationale behind this approach is often based on the need to support safety arguments that claim "all reasonably foreseeable risks have been identified". Logically, such arguments cannot be made without providing evidence to demonstrate that all conceivable or plausible types of failure or dysfunction have been considered. This consideration should occur at some level of design abstraction within the system for all elements of a system.

For this reason, many hazard identification analysis techniques are *model oriented*, relying on a functional model written in a suitable graphical or textual language. The use of system models, particularly graphical models, is highly valuable as it makes the estimation of the effort and duration for conducting a hazard analysis more predictable compared to relying solely on free-form design information. System functional models, such as functional block diagrams, signal flow graphs, state transition models, and control flow models, typically consist of symbolic elements representing flows, transformation processes, interfaces and other functional components of a system. The size of the model is usually finite, although certain models (e.g. railway networks) can be very large and the number and type(s) of model elements to consider can be unknown.

Additionally, many system models are *hierarchically organised*, into major subsystems, which contain minor sub-assemblies, which themselves can contain individual components. One of the major issues of functional hazard analysis is the combinatorial expansion of the number of failure conditions when analysing deeper levels of the design indenture levels of a system, it is also possible to approach the problem in the opposite direction. By moving higher in the design hierarchy and identifying larger subsets of the system, the number of elements to consider decreases, simplifying the analysis of failure/dysfunctional conditions. The art of safety engineering lies in balancing the effort required for hazard analysis with that of safety analyses at later stages in the system development process.

In the field of robotics, popular choices of graphical modelling languages are UML and the related language SysML [65, 73, 123, 124]. These languages, represented by dynamic or static diagrams, include use cases, sequence and state machine representations. The use case diagram is one of the basic diagram types of UML and is used to capture general aspects of user interactions and high-level objectives of a system.

Table 5.2 shows a subset of the use case diagram used in a sit-to-stand assistive task analysis conducted in a previous study [65]. The study employed a variant of the HAZOP technique. One drawback of the HAZOP is the identification of system parameters. To overcome this shortcoming, [64] proposed an approach called HAZOP-UML, implemented for physical human-robot interaction. The HAZOP-UML analysis of a sit-to-stand assistive task was implemented, and hazard identification through PHA and HAZOP-UML is presented in Table 5.3. However, it is worth noting that identifying of hazards and risk in complex interaction conditions, as emphasized by the guidelines in HAZOP [44], can be challenging Physically assistive robots for older adults operate in highly dynamic environments with unpredictable human needs and behaviour. These interaction requirements may not be appropriate through hazard analyses such as HAZOP.

5.2.4 Review of Previous Work in Hazard Analysis of Robots

For attempting to standardise collaborative robotics design, specifically for personal care robotics, the last review of the ISO 13482:2014 [22] includes some relevant guidance, however, this is quite generic and does not include specific issues relating to frail and vulnerable users, and the likelihood of change in their condition. To strengthen the ISO 15066:2016, several research projects have contributed to hazard analysis in physically assistive human-robot interaction. Some of these European projects are PHRIENDS 2006-2009, followed by its successor SAPHARI, 2011-2015. In PHRIENDS, the focus was on collision avoidance through reactive control and compliance design [81], [67]. The SAPHARI project [14] modelled to avoid collision between humans and robots rather than shape a coupled collaboration with the user. Physical assistive interaction would require uninterrupted physical contact and support from the robotic system. These are not tackled in SAPHARI or PHRIENDS.

Additionally, this interrupted physical contact and interaction would require an understanding of the users' needs and behaviour to highlight the interaction constraints subject to different scenarios. Older adults may present a variety of impairments, which can constrain the parameters of interaction. Hence, this is why general design requirements cannot fully cover the high variance in the limitations between the target users of assistive robotics. Therefore, given this significant gap, standard risk assessment methods in the literature such as **HAZOP-UML will fail to assess the complexity** emerging from different user needs and behaviour. The research in this area lacks a user-centred design perspective.

5.3 Finding from the Focus Group Studies for Safety in Physically Assistive Tasks

5.3.1 Participants and Care Homes

As part of **OS3**, focus groups were conducted in two different care homes in Bristol in the United Kingdom, with seven professional participants. The total years of experience working in care homes ranged from 8 to 23 years. The specific job roles involved were a manager of one of the nursing homes, nurses, physiotherapists, senior carers, carers and occupational therapists. These care professionals describe their experience as:

- Working closely with NHS and international equipment trust for care homes;
- Years of working with people with dementia, physical and cognitive disabilities;
- Years of training assisting older adults with mobility;
- Managing of care staff;
- Support of resident on rehabilitation programs and follow-up of work from physiotherapist;
- Motivating people with dementia to carry on with their daily activities.

The focus groups aimed to understand the hazards and risks identified by the professionals and how hazards are dealt with when assisting older frail people. Ultimately, we want to incorporate this knowledge into deriving an approach to assessing the situation after a hazard is detected and continue to assist safely. The assistive tasks of supporting standing up, sitting down and walking were used as examples to determine the concerns that require attention when assisting frail older people. The discussion focused on understanding the complexities a physically assistive robot needs to address by setting out any requirements for the system design to maintain safe adaptation to potentially changing user needs.

Nursing and care staff can provide a more hands-on approach to the problem and elaborate on hazard analysis with their years of experience. The aim is to uncover what the conventional hazard assessment methods are not seeing in the overall picture of physical assistive robots by questioning these experienced personnel. Correspondingly, our discussion highlights the gaps in the existing literature by posing important *what-if* questions specific to the care home scenario. We aim to shed light on the lack of understanding that arises when safety guidelines are formulated without considering the knowledge and procedures employed by professional carers. The methods described in [66] suggest that hazard identification techniques should be incorporated early in the design process and specifically address human interaction as a potential source of hazards. Developers can proactively design solutions that prioritize safety and mitigate potential hazards by considering and anticipating these risks. This simplified approach helps understand all the hazards and obtain further in-depth information about the assistive task. This interpretation of hazards is limited to the people designing the assistive technology. It is indeed a significant challenge for engineers and technical professionals to identify all the potential complications that may arise when interacting with vulnerable older adults in unfamiliar environments. In light of this challenge, nursing and care staff play a crucial role in providing a hands-on approach and leveraging their extensive experience to contribute to hazard analysis. In order to gather valuable insights, we engaged care-home professionals in critical discussions and analyses, seeking their perspectives on the following key aspects:

- Different scenarios of stand, walk and sit supports.
- Variations involved in the physically assistive tasks.
- Concerns and reflections on assistive technologies.
- Safety issues involved in performing the physically assistive tasks (the pre-condition, normal flow and post-conditioning of the task).
- Hazards and alternative ways to adapt the assistive task.

As a preliminary step, prior to the focus group sessions, professional carers were presented with a short video clip illustrating potential solutions involving physically assistive robots for sitting, standing, and dressing. Subsequently, the key aspects forming the basis of the discussion were introduced to all attendees in the room. Throughout the focus group sessions, the professional carers actively engaged in comprehensive discussions on each highlighted aspect, drawing from their substantial expertise and insights. To capture their thoughts and contributions, these were documented on sticky notes during the discussions. These written comments were then meticulously arranged and affixed onto large boards within the discussion room. Specifically, comments related to various tasks underwent further categorization into pre, during, and post-task segments, enabling a structured examination of considerations at each phase. The visible placement of these comments served as starting points for discussions, leading to the discovery of additional observations and crucial details essential in performing physically assistive tasks.

In all cases, the participants reported no contradicting opinions. Some of the hazards identified and variations in the task were different between care homes, but the overall approach and critical analysis of the assistive task were unanimous.

5.3.2 Interpretations of the Purpose of Assistive Tasks

In this section, an interpretation of the purposes of assistive tasks as seen by the caring professionals is provided. Three discrete situations for assistance emerged from the questions to the participants. Firstly, there is a psychological aspect related to the individual's motivation or mental state influencing their need for physical assistance in standing and walking. Acquiring independence by walking can help the individual keep a daily routine in the care home environment. Secondly, a physical aspect - moving is beneficial for the health of the musculoskeletal system, skin and overall well-being. It also relieves pressure and reduces tissue damage that results from prolonged immobility. Thirdly, a social aspect of the care home is attending dinner, getting dressed, visiting the health centre or dentist, or even going to social events and places in and outside the care home. Caring professionals argued that being unable to stand is closely associated with a cognitive and physical decline experienced by older adults. They noted that this decline is often noticeable not only to the individuals themselves but also to their family members and caregivers. The inability to stand can be an indication of various underlying health issues and can significantly impact the overall well-being and quality of life of older adults.

Furthermore, it was suggested that the level of physical ability does not always accurately reflect the amount of assistance an individual requires to perform a particular task. In this situation, it can be hard to accept the impact of ageing and the need for physical assistance from relatives and older adults. It is important to recognize that older adults may have limitations in certain areas but still maintain a level of independence in performing other daily activities, such as walking or completing tasks around the home. Providing physical assistance in these cases can help sustain their independence and overall well-being even if they require support for specific aspects of a task. This highlights the importance of having access to both physical assistance from caregivers and the assistance of technology that alleviate the burden on carers, particularly when considering the increasing elderly population. However, it is important to acknowledge that the complexities involved in these tasks often surpass the capabilities of any current technology. Therefore, it is critical to evaluate and identify any hazards arising from these complexities. Understanding the variations in assistive tasks is essential in developing appropriate technology and continually quantifying whether the technology and person can collaborate effectively and safely.

5.3.3 Interpretations of the Variations of Assistive Tasks

The insights provided by the nursing and care staff indicated that variations in assistive tasks primarily stem from the specific user's behaviour and needs at a given interaction time. Such variations are inevitable in real-world contexts. In all cases, participants emphasized that these variations depend on the type of impairments individuals have, as different cognitive and physical necessitate different approaches to the assistive task.

It was further explained that an individual's capabilities can vary frequently. For example, the balance may worsen in the evening due to fatigue, and medication cycles can affect the users' physical abilities and interaction capabilities. Additionally, it was noted that a person's physical abilities can be non-symmetric and change over time, particularly in cases of stroke patients where one side of the body is affected to different severity levels. Communication difficulties were identified as a common reason for altering the typical flow of physically assistive tasks in individuals with cognitive or stroke-related impairments.

People with cognitive issues may struggle to comprehend instructions provided by carers or nurses. To facilitate the movement of individuals with dementia, different preparations may be necessary. For example, when a person with dementia needs to go to the bathroom, switching the light in the target room can serve as a subtle indication of their destination, rather than just using verbal communication. On the other hand, people who have had a stroke may face challenges in expressing their needs. Another variation was changing moods, which can fluctuate from one day to another or even within a single day. An individual's likelihood to collaborate may vary depending on their mood and it was noted that people with dementia tend to experience mood swings more frequently.

Furthermore, a lack of willingness to cooperate can be triggered by random objects in people's environments, leading to a diminished sense of security. For example, the presence of a chair facing the older adult while being assisted into standing might be perceived as an obstruction. Attempts from carers to remove obstructions can result in objections or a lack of collaboration. Trust issues were also raised as a significant variation in the assistive task. Some residents may trust only specific carers because they feel safer with them. Not having access to these trusted carers can trigger a refusal to collaborate or cooperate.

In summary, these variations can apply to any assistive task. *Changing ability, balance, fatigue, weight, and mood swings require an adaptive interaction approach. The successful execution of this adaptation heavily relies on the carer's ability to identify the patient's current willingness to collaborate, understand the reason for the lack of collaboration and act accordingly to ensure the task is not disrupted and can be completed.*

5.3.4 How Caring Professionals Identify and Deal with Hazards

Table 5.1 presents a list of the main hazards identified by the carers and nurses. These examples of hazards emphasize the importance of identifying and addressing them when implementing a fully autonomous assistive robot. Figure 5.1 illustrates the modalities, tools and abilities as told by the caring and nursing professionals to assist, interact and collaborate safely when encountering these hazards (see Table 5.1).

Visual observation and inspection of the surrounding environment, older adults, and potential distractions are the primary methods for identifying most hazards. Tactile cues serve as feedback to help carers adapt to the physical interaction and determine the appropriate level of physical assistance. The expertise of carers in evaluating the current situation through tactile cues and comparing it with past experiences enables them to identify potential hazards and take timely action. Verbal interaction is another modality used to provide continuous instructions to the older adult and gauge their response, if any. This aids in identifying potential hazards before executing the assistive task and being prepared to address hazards specific to the user's condition.

A prominent theme emerging from the identified hazards is the complexity and influence of older adults' conditions and behaviour on physical actions. Accomplishing the task in such instances would require the assistive robot to possess sophisticated motion control capabilities. However, as discussed in section 5.3.3, irrespective of the degree of vulnerability of the older adults, carers consistently find ways to engage, assess willingness to collaborate, and provide appropriate assistance.

These observations suggest that the assistive robot's ability and ability to manage these complexities dictate which level of frailty and other conditions can be assisted by the assistive robot or be left entirely dependent on the carer. The variations described in Section 5.3.3 show that a fixed user model is insufficient in reflecting a person's needs, as these needs can change within the same day for the same assistive tasks. Figure 5.1 shows the importance of measuring and reflecting the older adult's ability to collaborate during the task. Each hazard identified in Table 5.1 and marked in column five of Figure 5.1 requires a measure of collaboration from the carer to be overcome and provide the necessary assistance safely. Once hazards are identified, carers can achieve the goal of the assistive task by acting accordingly and selecting an action that suits the patient's need at that moment. The capability to assess the older adult's ability to collaborate helps the carer to make real-time adaptations to the assistance provided and control the motion while ensuring the safety of the assistive task.

Table 5.1: A set of hazards identified by Nursing and Care Professionals

	Hazards Identified by Health Care Professionals
1	Failure to adapt speed of the task for patients with low blood pressure.
2	Patient commands not interpreted correctly.
3	Failure to adapt to patients' different abilities on both sides of the body.
4	The patient does not have appropriate support.
5	Failure of communicating continuous sub-goal of assistance
6	Failure to check for stability.
7	Failure of communicating which leg to use.
8	Disturbances from the environment.
9	Non-even floor levels.
10	Patient sudden changes of speed.
11	Patients might need to stop for catching their breath.
12	Failure to ask the patient to stop.
13	Patients with cognitive impairments are triggered to sit wherever even when there is no seating area around.
14	Patients with cognitive impairment might think that darker areas of the floor are non-levelled.
15	Patient can change their mind during the task.
16	Patient crash lands on the chair or in an inappropriate posture.
17	Inappropriate footwear and clothing for the assistive task.
18	Patient not turning appropriately to conclude the task.
19	Patient not placing hands for support in the right place.
20	Sitting chair is not appropriately set for the body shape and height of the patient.
21	Fall of the patient.
22	Patient reluctant to do the assistive task without holding a valuable item. This will cause instability if the equipment requires holding or using both hands.
23	The patient has a swollen foot - requires a change of footwear.
24	Patient with a lack of control of the lower knee requires more assistance.
25	The patient's standing chair does not have the brakes on.
26	The patient is not wearing his glasses - obstructed vision (user-model not valid).
27	The patient is currently in the medication cycle, which leaves them not able to collaborate (user-model not valid).
28	Patient's feet not in the right positions during pre-condition and post-conditioning.
29	Patient is still lying in bed requiring pre-conditioning.
30	Patient can have sudden sharp pains during assistance.
31	Patient shape and posture.
32	Patients with bent postures tend to hit the equipment with their head.
33	Patients distracted by their phone or surrounding environment - might stop to pick their item up while walking.
34	Patients keep hold of the assistive equipment while landing.
35	Patients hurt shoulders by pulling up with the assistive equipment.
36	Patients' ability and fatigue changes. (user-model changes)
37	Patients' posture on the chair requires more elaborate help as pre-conditioning.

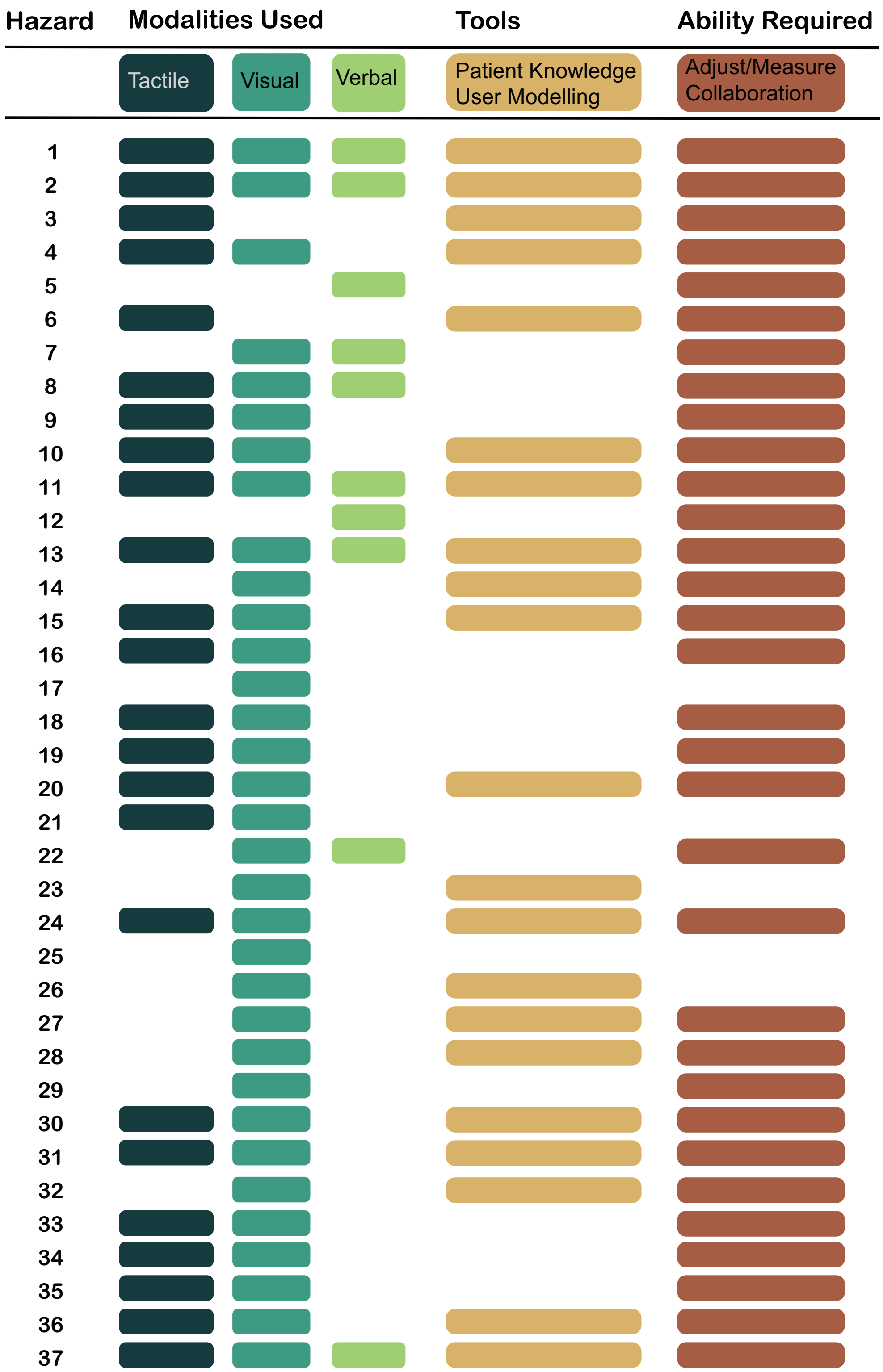


Figure 5.1: A graphic showing how the hazards (Table 5.1) are identified by the caring professionals and whether or not it is possible to adapt their interaction based on a collaboration intuition.

5.3.5 Feedback on a Prototype Robotic Solution for Assistive Tasks

The participants were shown a video of a prototype ceiling-mounted physical assistive robotic that would help frail patients with sit-to-stand and walk around a care home and asked to comment on their first impression, concerns, queries and enthusiasm about the assistive technology.

Immediately, participants highlighted that preparation needs to be considered before the task actually starts. Participants strongly emphasised that the assistive robot would need to adapt to a particular patient's profile and start with the correct preparation for the task and eventually, execution of the task, for the individual. Some of these preconditions are listed in the hazard list shown in Table 5.3.

One carer argued that the assistive device needs to be smaller to move around the furniture and environment. Some felt that such a device did not show ways in which it would be possible to adapt to different body types and respond to changes in the end-users changing ability throughout the day. Additionally, participants stated that continuous verbal communication and provision of instructions for the patient help them understand and enhance collaboration. More technical comments from the participants included: whether such technology could be charged anywhere in the home and whether a daily report could be generated about the decline or change in the ability of the patients.

It was acknowledged that having such an assistive robot could help patients and make them feel more confident and independent, even in their home environment. It was suggested that some patients, such as those with Parkinson's are still able to walk but not for long. These types of patients usually require the surveillance of a carer. Having such assistive devices can help free the time of a carer. The majority of participants agreed that such a device would help to increase the number of times patients can move around the care home since they will be no longer entirely dependent on the carers' presence. Participants also remarked that such technology could help provide a daily report of the patient's decline or improvement.

The main concerns raised were the lack of correct ergonomic support from the assistive equipment when performing the tasks. For sit-to-stand assistance in some patients, pulling up and putting pressure on the shoulders could be an incorrect way of accomplishing this task. Participants also raised concerns about older adults misusing this assistive device in their homes. One participant described the scene when a patient could be going around the home, holding onto the device while picking up stuff around the house.

User Case Name	**Standing up Operation**
Abstract	The patient stands up with the help of the robot
Pre-condition	The patient is sitting down The robot is waiting for the standing up operation Battery charge is sufficient to do this task to help the patient to sit down The robot is in front of the patient
Post-condition	The patient is standing up The robot is in admittance mode
Invariant	The patient holds both handles of the robot The robot is in standing up mode Physiological parameters are acceptable

Table 5.2: Use case described by UML hazard analysis method [66].

Hazard No.	**Description of Hazard through PHA and HAZOP-UML in MIRAS**	**Hazard identified by Carers**
HNI	Incorrect posture of the patient during robot use	Yes
HN2	Fall of a patient due to imbalance not caused by the robot	Yes
HN3	Robot shutdown during its use	No
HN4	Patient falls without alarm or with a late alarm	Yes
HN5	Physiological problem of the patient without alarm or with a late alarm.	Yes
HN6	Fall of the patient due to imbalance caused by the robot	Yes
HN7	Failure to switch to safe mode when a problem is detected. The robot keeps on moving.	No
HN8	Robot parts catching patient or clothes.	Yes
HN9	Collision between robot (or robot part) and patient.	No
HN10	Collision between robot and a person (not patient).	No
HN11	Disturbance of medical staff during an intervention.	Yes
HN12	Patients lose their balance due to the robot (no falling).	Yes
HN13	Robot manipulation cause patient fatigue.	Yes
HN14	Injuries of the patient due to robot sudden movements while carrying the patient on its seat	Yes
HN15	Fall of the patient from the robot seat	Yes
HN16	Frequent false positive alarms (false alarm)	No

Table 5.3: List of hazards not identified in the hazard analysis methods[66] (PHA and HAZOP-UML) but identified by Nursing/Care Staff

5.3.6 Comparison of hazards identified by professional staff and the standard HAZOP-UML

When considering altogether the individual hazard analysis and alternative flows of interactions, a total of 17% of these listed are related to interaction constraints, 28% were classified as technical systems requirements, and around 55% were classified to be user needs and behaviour dependent. Additionally, categorising the hazards collected from the focus group in terms of use case description, the majority of hazards were listed to occur either as a precondition or as alternative flow or exceptions of the assistive interaction. Preconditions, user needs and behaviours were highly interlinked when participants were commenting about the assistive task. Participants suggested that depending on the patient's needs, the precondition can change drastically. Furthermore depending on whether the patient has a condition such as Parkinson's or dementia, the alternative flow of the interaction can somewhat be predicted or reduced to result in fewer hazards. The use cases described by the UML approach shown in Table 5.2 describe the task of standing very superficially when compared with the safety assessment provided by the carers (see Table 5.1). This strengthens the original hypotheses that such methods are not capable of eliciting and analysing the complexity of such physically assistive tasks. Table 5.3shows the hazard analysis for the HAZOP-UML approach applied to the sit-to-stand task identified by a combination of PHA and HAZOP-UML. A more comprehensive overview of the hazards and requirements specified by the carers and nurses can be seen in Table 5.1. When comparing the hazard list from the PHA and HAZOP-UML [66] with the requirements and hazards identified directly by the care and nursing participants (see Table 5.2), a significant difference in the number and nature of hazards becomes evident.

Carers identified user needs and behaviour that can significantly change the interaction flow, revealing hazards that are completely overlooked in the HAZOP-UML (see Table 5.3). These observations emphasize the inadequate understanding of the patient's complexity in the interaction with physically assistive robots. Such findings underscore the limitations of current safety standards methods and emphasize the necessity of a user-centred design approach that incorporates input from all stakeholders in the application of physically assistive robots.

Ensuring the safety of physically assistive robots requires explicitly considering the insight and experience of care professionals. Consequently, a reevaluation of the HRI metrics and their determination becomes crucial. The identified shortcomings represent the 'unseen data' in the field of physically assistive robots, shedding light on the importance of addressing these issues for the development and implementation of safe and effective assistive technologies.

5.3.7 Potential Extension of Metrics in pHRI

The authors, Murphy et al.[109], presented a review of the 42 applied metrics for HRI. The taxonomy presented here does not cover all the requirements as highlighted during the focus groups for physically assistive tasks. The *safety* and *reliability* metrics do not include the required adaptivity of the system in response to the complex and changing needs of the end-user. The variations in the physically assistive task described by the participants required continuous adaptions to a changing set of *human model* metrics, even over the same day. These variations require *reliable* metrics which can determine the current state of the *human model*. In order to define these reliable metrics, clinically qualified people such as psychologists, physiotherapists and occupational therapists, need to identify measures that can enable an adaptive interaction. The **psychological** conditions of the user can highly affect the safety of the human in the interaction, particularly in the context of pHRI. From the evaluation of Tables 5.1 these measures can be described as panic, intent, distraction, illness, pain level, anxiety, preparedness, alertness and need for reassurance. In human-human interaction described by the participants, these were all conditions to which carers and professionals recognised and responded, in order to safely assist the older adults. Furthermore, **physiological** measures of the human such as fatigue level, blood pressure, medication cycles, physical conditions and impairments are also subject to variations. The **psychological** and **physiological** metrics together with the *human model* should be able to define a **level of assistance** required by the human. Ensuring measurable and representative measures for these requirements will endorse the metrics of *human, safety, co-activity and reliability* as presented in [109] from a more practical approach for pHRI.

Furthermore, the complexities that arise from assistive tasks have uncovered measures that require further discussion with professionals in order to identify if possible thresholds on **psychological** and **physiological** can, or should be defined to limit the use of the physical assistive robot for a particular subset of older adults. These restrictions are due to the fact that the complexity of the task is highly affected by the **psychological** and **physiological** state of the user and it is realistic to have an added metric of **eligibility** of the end-user so that the pHRI can take place safely and reliably. In this way, the complexity of the human model can be bounded within measures from which the user requirements could be classified as either being eligible for the assistive interaction or not, or even to what extent. The taxonomy for pHRI presented in [32] is based on the fact that the robot behaviour adaption is defined through a user model and is stated to not require any other adaptive behaviour once the user model is selected. The physically assistive task presented by the carers suggests that in some cases the user profile might also change during the day and hence adaptivity in response to specific **psychological** and **physiological** measures is critical to maintaining safe interaction.

Henceforth, the metrics for safety in pHRI should be expanded and underpinned by specific dimensions of the task complexity, together with a user-centred design approach that enables structured metric-orientated studies to be carried out with professionals and end-users.

5.4 General Discussion

5.4.1 Findings

In this OS3, the participants consisted of caring and nursing professionals. The primary objective of this chapter was to identify the requirements and conduct a hazard analysis related to physically assisting older adults. This work was conducted to address the limitations highlighted in the previous chapters which emphasized the importance of integrating HF, HS and environmental factors in evaluating the input modality through the robot factors. By conducting this study in a real-context environment through the lens of professional carers, the significance of establishing these connections becomes evident and provides insight for future directions.

The use of physical assistive robots aims to establish valuable support for the growing ageing population. Dealing with a range of different types of impairment, physical and cognitive needs, imposes the necessity of safe, close-proximity interaction. These observations have described the safety analysis techniques that nursing and care staff follow when assisting patients. The main contribution of **OS3** has been to highlight that several complexities that arise from the needs and behaviour of the patients are not adequately taken into account when model-based safety analysis techniques are applied. This analysis mainly evaluates the assistive task based on the robot's ability to detect or avoid these hazards. Furthermore, we have seen that the current metrics of safety, reliability and human model are not sufficient to capture this complexity and hence fail in creating safe and usable HRI. Therefore, we identify the complex requirements of physically assistive tasks and show how metric-oriented studies that seek to understand and model the human element of HRI can lead to more comprehensive metrics which create repeatable and effective HRI. The argument made here and findings from the observation study address **RQ5a** and **RQ5b** highlight the limitations in the current approach to physically assistive robots.

When considering the various patients' needs and behaviours, and analysing how they would actually use this assistive technology in real-world environments, then further hazards start to be identified. The evaluation of the nursing and care staff created several new use cases not considered by the standard methods currently used. This hazard identification from the patient's point of view would require adequate adaption and additional sensing capability from the assistive robot. The current regulation shows a superficial assessment of physical assistive interaction with robotic systems. The model-based safety analysis technique is mostly inapplicable without incorporating the ability to adaption to the user needs and behaviours. The feedback and points raised by the care and nursing staff show the importance of evaluation of the human-in-the-loop in the aspects of interaction and technical design. *The inclusion of these aspects together with the acquisition of new skill sets from professionals to define these requirements will make the research of physical assistive robots safer.* These arguments continue to further answer **RQ5b**.

One prominent finding from the hazards and requirements identified in this study is that carers consistently assess the state of the individual and do not assume that an older adult will exhibit optimal behaviour, even within the same day. The dynamic nature of the older adults' capabilities and behaviour necessitates ongoing evaluation and adaptation by the carers. This highlights the importance of recognizing and responding to the individual's current condition and needs rather than relying on assumptions or generalizations. The findings presented in this study directly address research question **RQ5c**, as they demonstrate that carers never assume optimal behaviours when providing physical assistance to older adults. The evidence provided indicates that carers recognize the dynamic nature of the individuals they care for and continuously assess their current state and needs. Furthermore, these findings also support the answer provided to research question **RQ2b**, which was discussed in Chapter 3 and Chapter 4. Carers emphasize the importance of considering the contextual factors in the environment when providing physical assistance, as these factors continuously change and require meticulous hazard analysis to ensure safe task execution, particularly in close proximity interactions.

5.4.2 Lessons learnt

One concept that continuously emerged from this observational study was the following:

- That irrespective of the degree of vulnerability of the older adults, carers always try to create ways to engage and measure collaboration while assisting.

Collaboration in the context of physically assistive tasks is a complex aspect that plays a crucial role in determining safety. While evaluating collaboration can be challenging, quantifying it can serve as a key determinant of safety in these tasks. The next chapter (Chapter 6 of this research focuses on developing a methodological approach to designing human-robot experiments specifically tailored to quantify this measure of collaboration. By conducting more realistic human-robot experiments, such as CS2, it is possible to infer and construct this measure using the modalities employed in each task.

Incorporating these insights into future studies will not only contribute to a better understanding of user experience during human-robot interaction but also advance research in safety. To ensure the safe deployment of assistive robots, it is crucial to carefully consider the input and feedback from nursing and care professionals who possess experiential knowledge in these tasks. Adopting a co-design approach that involves their expertise and incorporates their insights will help address the complexities involved and shape the development of technology in this field.

5.5 Summary

In this chapter, we asked: *What-if* assistive robots can learn and adapt the metrics carers use to achieve a safe and successful interaction? (see Figure 1.1). Firstly, we examined the perspectives of caring professionals on the importance of physical assistance in providing humane care for older adults. Their insights shed light on these tasks' laborious and complex nature, emphasizing that they are multifaceted due to the numerous variants that can arise for a single older adult during an assistive task. Carers stated that changing ability, balance, fatigue, weight, and mood swings require an adaptive interaction approach. The successful execution of this adaptation heavily relies on the carer's ability to identify the patient's current willingness to collaborate, understand the reason for the lack of collaboration and act accordingly to ensure the task is not disrupted and can be completed.

Secondly, carers identified a long list of hazards that can occur in real-world environments, specifically in care homes. These hazards encompass a wide range of potential risks and dangers that carers need to be aware of and address to ensure the safety and well-being of older adults. These observations suggest that the assistive robot's ability and ability to manage these complexities dictate which level of frailty and other conditions can be assisted by the assistive robot or be left entirely dependent on the carer. These observations also emphasize the inadequate understanding of the patient's complexity in the interaction with physically assistive robots. Such findings underscore the limitations of current safety standards methods and emphasize the necessity of a user-centred design approach that incorporates input from all stakeholders in the application of physically assistive robots.

Carers have the ability to overcome these limitations by constantly evaluating the situation and examining whether their perceived level of collaboration and the current frailty of the older adult actually align. They actively assess and reassess the individual's needs and capabilities, making adjustments as necessary to ensure a safe and successful interaction. As seen in Figure 5.1 it is depicted that carers are able to overcome many hazards by measuring and assessing their perceived level of collaboration. This measure of collaboration serves as a crucial indicator for carers to gauge the older adult's willingness and ability to engage in the assistive task. Cares use input modalities to assess this. For Chapter 6, the input modality of human movement is specifically examined in this context.

CHAPTER 6

HUMAN MOVEMENT AS A 'COLLABORATION MEASURE' IN COMPLEX PHYSICALLY aHRI

The work presented in this chapter aims at achieving the ultimate goal of the thesis: to use the input modality of human movement as a measure of collaboration during a physically aHRI for a CPCI. To do so, the dataset from CS2 is further analysed to provide knowledge about the human state. This can be done since Chapter 4 has demonstrated that cognitive overloading and distractions can result in dressing failure due to a non-collaborative approach from the human. Therefore, the human movement dataset of CS2 contains both collaborative and non-collaborative human movements for a dressing task. By performing feature extraction on this dataset, it becomes possible to distinguish between these collaborative states. Consequently, we utilize feature extraction on the dataset to illustrate that these collaborative states can be identified through a projection onto a latent space. Latent spaces have recently been employed in physically aHRI and human movement evaluation algorithms to provide insights into the state of humans.

The taxonomy that defined the interaction safety at the level of complexity of CS2, is the following:

$$\textbf{CS2}: \{T_r\} \cap \{T_h\} \neq \emptyset \textbf{ and } D = F(R,H)E(.). \tag{6.1}$$

The aforementioned taxonomy was validated in Chapter 4 and Chapter 5, where we gained insights into handling complex tasks. The risk to physical safety stems from unidentified environmental factors. The findings presented in Chapter 5 concluded that the risk to physical safety arises from environmental factors that remain unknown. This was further supported by the taxonomy derived from the observation study, **OS3:** $\{T_{r_{carer}}\} \cap \{T_h\} \neq \emptyset$ **and** $D = F(R_{carer}, H)E(.)$, indicating that professional carers are essential in ensuring physical safety as they can consistently identify risks in the environment that may impact the physical safety of older adults, whether directly or indirectly. During physically assistive tasks, the robot must synchronize and adapt to the human arm's position. Consequently, any element in the surrounding environment can affect human cognition and movement (see to Chapter 4). The results from the last two chapters clearly indicate that the complexity of interaction outlined in Chapter 3, as represented by its taxonomy, **CS1:** $\{T_h\} \ominus \{T_r\} = \{T\}$ **and** $D = F(R)E(k) + F(H)E(.)$, cannot ensure the necessary physical safety in complex physically aHRI. Consequently, if older adults are to utilize such physically assistive tasks, research should focus on quantifying the collaborative state through multiple input modalities to ensure physical safety. This thesis primarily focuses on human movement and its impact on safety, and this collaborative knowledge can be presented through latent spaces. Feature extraction was initially applied to the human movement dataset to achieve such knowledge in a latent space. It was necessary to differentiate between smooth movements in *Part One* of the experiment and the fidgety and shaky movements during *Part Two* and *Part Three*. This approach enables us to ensure that if we obtain a good projection on the latent space then it can actually represent movement in these different parts of the experiments and, therefore, in different collaborative states.

Parts of this work presented in this chapter are in the following publications:

A. Camilleri, J. Hong, S. Dogramadzi, and P. Caleb-Solly, **Towards establishing a 'collaboration' Measure for Coupled Movement in Close-Proximity Human-Robot Interaction**, in *Integrating Multidisciplinary Approaches to Advanced Physical Human-Robot Interaction*, ICRA 2020, Virtual Conference, 2020.

A. Camilleri, S. Dogramadzi, and P. Caleb-Solly, ***A Study on the Effects of Cognitive Overloading and Distractions on Human Movement During Robot-Assisted***

Dressing, *Frontiers in Robotics and AI* - Human Movement Understanding for Intelligent Robots and Systems, (2022).

6.1 Introduction

To ensure safe physical pxHRI in physically assistive tasks, robot motion planning should adapt to changes in human behaviour. Probabilistic confidence-awareness models can predict human movement with confidence while learning the variance in human movement is crucial for safe trajectory planning. External distractions and cognitive overloading can alter human skill and interaction, necessitating evaluation for long-term safety.

For robust long-term prediction and adaptation of human movement, motion planners must ensure collision-free trajectories and proper coupling between robot and human movements. In the context of CPCI, collaboration measures in trajectory comparison enhance overall safety. Synchronizing movement is key to successful interaction, but knowing if the human wants to collaborate is a requirement for physical safety in assistive tasks (see Chapter 5)

The presented collaboration measure captures the coupling between robot and human movements and acts as an additional safety metric for trajectory planning. Controlled experiments in an assistive dressing scenario demonstrate its usefulness, especially in detecting the lack of collaboration caused by one-off events. This measure provides insights beyond variance in learned movement skills.

Safe close-proximity human-robot interaction depends on recognizing and adapting to changes in human behaviour. Collaboration-based trajectory prediction, facilitated by a measure of coupling, enhances intelligence in motion control. Understanding humans' behavioural responses to disturbances are crucial for achieving robustness and safety. The presented work utilizes a human-robot interaction experiment to study changes in behaviour and collaboration, showcasing the representation of collaborative and non-collaborative movements in a Latent Variable Model. This model captures the changes in collaboration during physically assistive interactions, contributing to safer and more efficient pxHRI.

The development of autonomous systems that assist humans in various tasks, including elderly care and hospitality, requires safe controllers capable of effectively interacting with humans. Close-proximity interactions pose challenges in accurately predicting human movements and behaviours. In order to ensure safety in such interactions, robot motion planning needs to adapt to real-time and long-term changes in human behaviour. This chapter considers the long-term aspect and focuses specifically on the assistive task of dressing (CS2), which involves close-proximity and physical contact with humans.

In close-proximity interactions, physical contact-based adaptation relies on minimizing feedback parameters such as force and garment entanglement [82, 83]. However, in situations where force feedback is unavailable, synchronization of movements becomes crucial. To achieve safe close-proximity interaction, it is beneficial to have a measure of collaborative behaviour based on realistic human behaviour. Collaboration-based trajectory prediction has been explored in literature [80], utilizing simulation-based approaches and collaboration criteria. Interaction primitives have previously been used to correlate human and robot's movement [16], however, non-collaborative behaviour has not been extensively studied in these scenarios.

In order to ensure safety in close-proximity human-robot interaction, robot motion planning needs to recognize and adapt to the human movement, both in real-time and long-term. These characteristics, need to be applicable in all contexts and situations to be certified as a safe interaction. The focus of this chapter is on the assistive interaction of dressing which by nature takes place in close-proximity and eventually in physical contact with the human. In the context of physical contact, adaption will be implemented by searching for a minimum in a space that is parameterized by feedback that characterizes physical contact; such as force or garment entanglement as presented in [82, 83]. In close-proximity, force feedback is not available and adaption can only be achieved through inferred synchronization of the movement. In this context, movement adaption can only be certified safe if prior observations of the human's motion can somehow be modelled in situations that hinder synchronization. Hence, in close proximity interaction having a measure of collaborative behaviour is extremely beneficial in the context of assistive robots. A similar approach can be seen in other literature where collaborative behaviour estimation between pedestrians and vehicles was implemented by the authors of [80]. In order to model the collaboration-based trajectory prediction simulation was used to extract trajectories that go along or against a set of collaboration criteria. Similarly, in close-proximity assistive robotics this collaboration behaviour would also be beneficial but needs to be based on a realistic human behaviour. Interaction primitives have previously been used to correlate human and robot's movement [16], however non-collaborative behaviour has never been examined in these scenarios. To be able to acquire such knowledge we need to create a context in which human movement data is collected during close proximity interactions while collaboration is impeded. This context would enable us to define the criteria of collaborative and non-collaborative behaviour.

Our aim is to be able to detect changes in human behaviour and hence human motion. As seen in Chapter 4, neuroscience research has provided frameworks that link human behaviour and movement, such as the free-energy principle. These frameworks emphasize the active role of the human brain in minimizing differences between their model of the world and sensory perceptions. Distractions and cognitive overloading can affect motor control and, consequently, human movement. The presented work verifies these effects through experiments conducted in the dressing task, as explained in previous chapters. One principle is that of the free-energy principle which can be linked to information theory, optimal control theory and game theory [56]. These models state that the human brain actively makes observations and tries to minimise the free-energy of their model of the world . This means that if a surprise occurs their reaction is the effect of trying to minimize the differences between their model of the world and their senses and associated perception. Subsequently, if these surprises in interaction can be a result of distractions and cognitive overloading then we can state that their motor control and hence movement will be affected. This effect of movement will enable us to observe human through the collaborative and non-collaborative behaviour aspect, this in fact was verified both in Chapter 4 and Chapter 5.

This chapter continues to analyse the dataset presented in Chapter 4. The hypothesis on which this human movement dataset was created is that behaviour changes occur between distracted and non-distracted instances of the dressing task. This change in behaviour is reflected in human motor control and arm movement in relation to the robot's end effectors. By modeling the latent variables in this high-dimensional dataset, it becomes possible to distinguish between collaborative and non-collaborative behaviour. This energy-based model can be used as part of a forward model in the context of CPCI to ensure collaborative adaptation. This is ideal because this interaction model will be based on a self-supervised approach that measures the compatibility of the input to the energy function. The low-energy areas will represent the points, which show collaboration, and high-energy points will represent the non-collaborative observations. Consecutively, if this hypothesis is verified predictive forward models can be easily built on these self-supervised predictive world models [95].

6.1.1 Research Questions

In summary, three research question will be investigate in this chapter through the human movement dataset CS2:

- *Can we create a measure of collaboration between the human and robot while performing a close-proximity interaction?*
- *Can we measure in any form these similarities in the collaborative and non-collaborative instances during the task?*
- *Can we couple the robot and human movement?*

The research questions in this chapter aim to address the research question **RQ6** whereas **RQ7** will be discussed in the chapter 7 based on the findings in this chapter.

RQ6: Following from **RQ4** and **RQ5**, how can such prior knowledge be used to couple the human movement and robot's motion planning to guarantee safety in the context of disturbance?

RQ6a: How can the variations in human movement be modelled as a prior knowledge?

RQ6b: Can a measure of collaboration be created from this prior knowledge to indicate a lack of synchronisation and hence a possible failure in the interaction?

RQ7 Ultimately can such collaboration measure be embedded and modelled in the robot's motion planning?

6.1.2 Contributions

In answering the above-mentioned research question, the following contributions are made:

- A similarity evaluation between the robot and human movement during an assistive dressing task CS2.
- A latent space visualization that shows that the human movement modality can incorporate the human collaborative and non-collaborative state.

6.1.3 Methods

This section will explain the approach and take on the human movement dataset from CS2 in order to do the similarity evaluation and the latent space projection. Initially, a summary of the case study will be repeated, followed by a technical take on the human movement dataset, the feature engineering extracted and the approach for the similarity and latent spaces. The assistive task in CS2 is that of being dressed with an outer layer of clothing. The human movement is recorded through the use of a motion capture Xsens Suit [132]. The environment in which the interaction takes place was controlled. This allowed us to generate a dataset of human movements and observe change in behaviour due to the changes in the surrounding environment. These changes were due to cognitive overloading and distractions. The change in behaviour also led to a lack of synchronisation between the human and the assistive robot. The cognitive overloading and distractions also led to failures in the assistive task. For safety, it is critical to be able to predict these failures and have a better understanding of what variations in movements are due to reduced human attention. Figure 4.2 shows the overall experimental layout. A total of 13 participants took part in the experiment, with 30 dressing iterations each. The experiment had three parts, with 10 iterations in each part. *Part One* consisted only of the dressing task while *Part Two* and *Three* consisted of cognitive overloading and distraction respectively. *Part two* of the experiment had the cognitive overloading timed to coincide with the initial phase of the dressing iteration. At this initial phase, only close-proximity movement took place and hence no physical contact. The cognitive overloading was introduced in *Part Two* with the purpose of distributing the participants' model of the world previously built in *Part One*. Therefore the cognitive overloading would result in a 'surprise' in the interaction. Hence the majority of the dressing iterations in *Part Two* resulted in a failed assistive task even though the participants were fully able to collaborate in *Part One*. The results of the experiment, in terms of failures and users' responses to the dressing task, are explained further in our previous work [29].

The observations of failed collaboration after participants were already familiar with the task indicate that collaborative and non-collaborative behaviour identification is a synonyms for safety. Hence to ensure safety, having prior knowledge of how coupled movement can vary is critical. Such knowledge should be a representation of coupled movement, which is minimized when collaborative behaviour is present and maximized when non-collaborative behaviour is adapted. The dataset collected from the experiment represents a time-series data of the robots' end effector and human movement. Figure 4.2 shows the timeline of one dressing iteration. The close-proximity collaborative behaviour is the evaluation of movement of the right arm until it is restricted in the garment, as shown in Figure 4.2.

6.1.3.1 Human Movement Trajectory Dataset

For each dressing iteration, the dataset consists of the right and left robot end-effector trajectories $\mathscr{T}_R$ which is represented as a set of quaternions from time $t = 0 \dots T$ and human pose J_1^N where N is the number of joints recorded from the motion capture. For the human trajectory $\mathscr{T}_H$, Each joint n is respectively represented by $[\mathscr{T}_{H_n}]_0^T$ as a series of position $p_n = (x_n, y_n, z_n)$ and a quaternion representation of the frame rotation at each joint as a series of $q_n = (a_n, b_n, c_n, d_n)$ for every trajectory $\mathscr{T}_H$. For simplicity, only the right end-effector and the right arm of the participant are used to evaluate the collaborative and non-collaborative movement.

Features were extracted from the trajectories of the human pose ($\mathscr{T}_{H_n}$) using a sliding window of size w along the time-series creating w_i windows, where $i < T$. We are interested in highlighting the difference in the right arm movement of the human while collaborating with the robot's right end-effector movement. The feature engineering focuses on statistical features of the movement of the joints J_1^N alone or with respect to the robot's movement during the close-proximity interaction. The features extracted over each w_i for every element of J_1^N are:

- *Mean*: the average value of the joints J_1^N over the w_i,
- *Median*: is the middle value, in w_i for each joint, when the data is arranged numerically, (averages if even number in w_i),
- Standard deviation: a measure of how spread the movement is over w_i,
- *Variance*: a measure of variation in joint angles or positions for the values of the movement in w_i,
- *Interquartile Range*: a measure of statistical dispersion over w_i.
- *Skewness*: the distortion of the movement over w_i,
- *Kurtoisis*: the peakness of movement over w_i,
- *Median Crossing*: the total number of movement changes below or above the overall median in the whole iteration,
- *Mean Crossing*: the total number of movement changes below or above the mean in w_i,
- *Wasserstein distance:* measure between human-robot movement,

- *Pair-Wise Correlation*: the measure of correlation in between the three joint (arm, hand and elbow) of the right arm over w_i.
- *Relative Entropy*: measure between of by how much the distribution of the human movement differs from that of the robots trajectory.

The relative entropy KL between robot and human arm trajectories is generated from the probability distribution using the sliding window approach. The use of KL divergence has been previously used to minimize the difference between the learned trajectory and the currently executed trajectory as presented in [45]. This requires the generation of two probability distribution, one for the right end-effector trajectory representation $p(\mathcal{T}_r)$ and another for the right human arm trajectory representation $p(\mathcal{T}_h)$. The mean and co-variance of each dimension of a trajectory $p(\mathcal{T}) = p(x_1,...,x_T)$ are used to create the probability distributions $p(x_r)$ and $q(x_h)$ respectively. Hence the KL, can be represented as:

$$KL(p(x_r), q(x_h))$$

and

$$KL(q(x_h), p(x_r))$$

Therefore, the KL divergences is calculated as

$$KL((p(x_r)||q(x_h)) = \int p(x_r) \log \frac{p(x_r)}{q(x_h)} dx \tag{6.2}$$

The rest of the features were chosen based on previous research as presented in the literature [168] and [145] who used similar features to recognise activity from human motion and to differentiate between motor skills. The hypothesis behind creating this feature space is that there are different patterns in the style of arm movement during the different parts of the experiment. Such feature engineering increases the dimensionality of the space representing the collaborative task. This resolution helps to create a distinction between the primitive skill used for the same collaborative task at different levels of collaboration by the user. A latent space representation of such features would allow to verify this hypothesis by being able to discriminate between the dressing iteration in each part of the experiment and hence between collaborative and non-collaborative behaviour.

The objective is to create a 'Collaboration Measure' policy ϕ_{cm} that needs to be maintained at a minimum during CPCI in physically aHRI when the user is fully collaborating with the robot. This policy will act as a state-action pairing checking; hence this would comprise an energy function f that provides information based on its current value on the collaboration state (cs) of the human HS.

$$\phi_{cm} = arg\ min_{cs}\ f(cs) \tag{6.3}$$

where f(cs), represents an energy function that compares the robot's trajectory state with the human movements observed at any state during the assistive task.

$$\phi_{cm} = arg\ min_{cs}\ f(\mathcal{T}_R, \mathcal{T}_{Hobs}, \mathcal{T}_{Hcm}) \tag{6.4}$$

where $\mathcal{T}_R$ represents the robot's predicted trajectory, $\mathcal{T}_{Hobs}$ represents the observed human arm trajectory and $\mathcal{T}_{Hcm}$ represents the predicted human arm trajectory based on the ideal cooperative interaction. $\mathcal{T}_{Hcm}$ is represented by the trajectories recorded in *Part 1* of the experiment.

$\mathcal{T}_R$ and $\mathcal{T}_{Hobs}$ is information gathered from cases studies similar to CS2. $\mathcal{T}_{Hcm}$ is the future prediction of human movement as shown in case study CS1. Therefore, the state of $\mathcal{T}_R$ with respect to $\mathcal{T}_{Hobs}$ is the direct relationship to the policy ϕ_{cm} . This implies that the robot's state (represented by its trajectory $\mathcal{T}_R$) during different phases of the assistive task and the corresponding human reactions through movements (represented by $\mathcal{T}_{Hobs}$) determine whether an ideal cooperation occurs or not. In CS2, the ideal cooperation refers to the human movements observed during *Part One* and the non-ideally cooperation is those movement observed in *Part Two* and *Part Three*. Equation 6.4 is the policy that sets the rule for physical safety in the assistive tasks. To guarantee this the energy function which gathers the information from the observed trajectories at the current state of the robot and human movement need to be at a minimum. This is as required by the equation 6.1, that suggest that in order to ensure physical safety, incorporation of the observed human trajectory need to also include knowledge about non-optimal behaviour. In this chapter, we evaluate two approaches for such function $f(\mathcal{T}_R, \mathcal{T}_{Hobs}, \mathcal{T}_{Hcm})$ designed to represent the predominant trajectory matching, considering how human movement is affected by distraction and cognitive overloading. This indicates that the energy function will yield a lower value when the state-action pairing from the observed trajectory $\mathcal{T}_{Hobs}$ is similar to *Part 2* when compared to a successfully dressing trajectory $\mathcal{T}_{Hcm}$ from *Part 1*. These approaches are explained in Sections 6.1.3.2 and 6.1.3.3.

6.1.3.2 Similarity Measure Modelling

The $f(\mathcal{T}_R, \mathcal{T}_{Hobs}, \mathcal{T}_{Hcm})$ will represent the attribute of the collaboration measure mentioned above to measure synchronization between the $\mathcal{T}_{Hobs}$ human arm trajectory and the $\mathscr{T}_R$ robot, and a measure of how the $\mathscr{T}_{Hobs}$ human arm trajectory is compared to a known skill $\mathscr{T}_{Hcm}$. The similarity measures need to be defined as either distance measures or the KL divergence. For example, if the KL divergence results are the prominent way of distinguishing the collaborative nature between the human ideal skill and the observed skill then Equation (6.4) can be represented as:

$$\phi_{cm} = arg\ min_{cs}\ f(\mathscr{T}_{Hobs}, \mathscr{T}_{Hcm}) \tag{6.5}$$

$$\phi_{cm} = arg\ min_{cs}\ (KL(p(\mathscr{T}_{Hobs})||p(\mathscr{T}_{Hcm}))) \tag{6.6}$$

The results from this task will inform the selection of similarity measures between the trajectories. The most appropriate results will be selected to be included in the 'collaboration measure' policy ϕ_{cm}.

6.1.3.3 Latent Space Modelling

The features extracted above represent a dataset which is high-dimension and non-linear required to describe human behaviour. The Gaussian Process Latent Variable Model (GP-LVM) [147] can efficiently project human behaviour onto a 2-D latent space while preserving most information in the high-dimensional data. These features make the GP-LVM suitable for projecting these cooperative and non-cooperative movements for close-proximity movement evaluation.

Firstly, a Gaussian Process (GP) is created which maps the high-dimensional dataset $Y = [y_1, ..., y_I]^T$ to a low dimensional latent space $X = [x_1, ..., x_I]^T$, such that:

$$y_j = g(x_j) + \epsilon, \quad \epsilon \sim \mathcal{N}(0, \beta^{-1} I) \tag{6.7}$$

where $y_j \in \mathbb{R}^M, x_j \in \mathbb{R}^N$, M and N are the dimensions of the respective datasets, M is the number of samples representing the feature dataset and g denotes the GP mapping. The latent variable is optimized by calculating the marginal likelihood for the observed data and is defined by:

$$p(Y|X,\theta) = \frac{1}{\sqrt{(2\pi)^{IM}|K|^M}} e^{-\frac{1}{2}tr(K^{-1}YY^T)} \tag{6.8}$$

where θ is the RBF kernel hyperparameter, K is the kernel matrix constructed from X and θ. Consecutively, the GP-LVM maximizes the likelihood of the predictions of the model given the dataset Y by finding the values of the kernel K. For the cooperative and non-cooperative projection onto the 2-D latent space our dataset Y is the features engineered from the human movement and robot's trajectories.

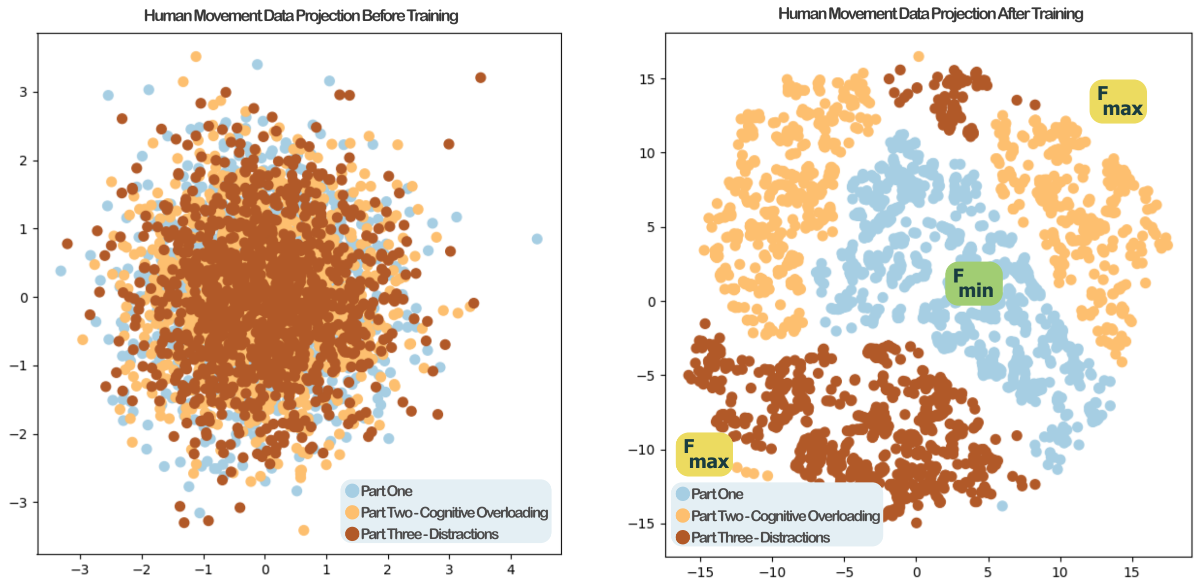


Figure 6.1: Feature engineering human movement before and after GP-LVM training. Sub-Figure B (the figure on the right) is showing the possibility of an energy-based function based on the projection of the data points on the latent space. The central part shows the desired movement whereas the other part shows the distracted and cognitive overloading part.

6.2 Results

6.2.1 Latent Variable Space Modelling

Figures 6.2, 6.3 and 6.4 show the visualisation of the CS2 dataset after the feature extraction using a sliding window approach previously explained. Each subplot represents the feature space of each participant. The three different colours show the projections of each iteration during the different parts of the experiment. The Gaussian process latent variable model (GP-LVM) projection provides an appropriate distinction of the movement features. The projection on the latent space suggests that the feature engineering from the data captures differences in the elemental movement. Furthermore, it also suggests that in fact the collaborative and non-collaborative behaviour in performing the assistive task can be distinguished. The cognitive overloading or distraction change in behaviour is reflected in a difference in movement.

Such latent space can be used to further create an energy-based policy based on the aggregated data points on this space. This means that creating an energy function ϕ_R that is minimized to maintain a collaborative behaviour allows us to base adaption on the observation that takes into consideration lack of collaboration behaviour which can be critical for safety in close-proximity interactions. Henceforth in order to allow for a forward predictive model based on this self-supervised approach, the energy-function needs to have a minimum in the points which represent *Part One* of the experiment. These points are the points that represent a highly collaborative behaviour while the remain point on the latent variable represent a less collaborative behaviour. Figure 6.1, shows the space before and after training. In the sub-figure 6.1B, examples of how the minimum and maximum energy values for an energy function f can be applied is shown on the latent space itself. Such results validate a complete experimental cycle, from experimental design to data collection and feature extraction, that can be used to address the unknowns in the environment and long-term interaction for future physically assistive human-robot interaction (aHRI). The results shown here do not demonstrate the energy function itself, but they illustrate a space where each projected human movement can be assigned a value based on the collaborative state of the human. It shows that this approach can provide valuable insights into the collaborative human-robot interaction through the input model of human movement.

These results also demonstrate a potential solution for equation 6.1 because the robot can receive information about the human state during the assistance. Moreover, professional carers in OS3 have emphasized the importance of ensuring physical safety by ensuring the willingness and active collaboration of older adults. The approach of CS2 and the use of feature engineering highlight how this can be achieved through input modalities that capture human movement. This approach holds significant value, especially considering that many older adults may experience difficulties in using verbal communication as an easier modality.

6.2.2 Similarity Measure as KL divergence between Human and Robot in CS2

The evaluation of $f(\mathscr{T}_R, \mathscr{T}_H)$ was implemented using the KL divergence between the robot end effector trajectory and the human movement in the right arm. These results provide an indication on whether the coupling of movement between the robot and human trajectories can contribute to the 'collaboration measure' and hence lead to an overall indicator of safer interaction.

Figure 6.5 shows the relative entropy between the robot trajectory and the human arm. The $KL(p(x_r), q(x_h))$ and $KL(q(x_h), p(x_r))$ were calculated for two joints of the right arm of four participants with respect to the robot's right end-effector. Each subplot in

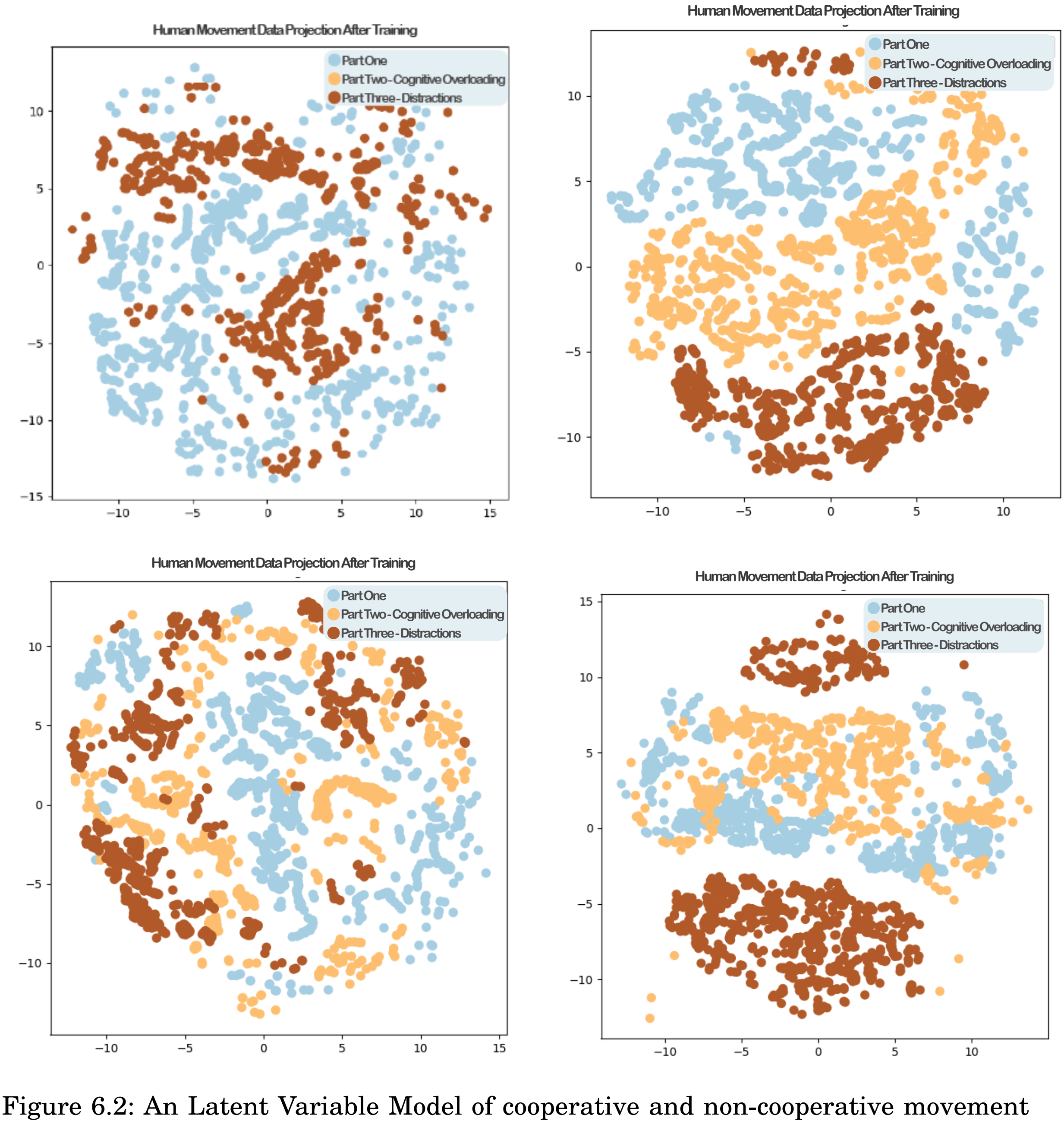


Figure 6.2: An Latent Variable Model of cooperative and non-cooperative movement created from the human and robot movement dataset based on features explained in section 6.1.3.1. The feature spaces represent the movements of four participants using GP-LVM representation.

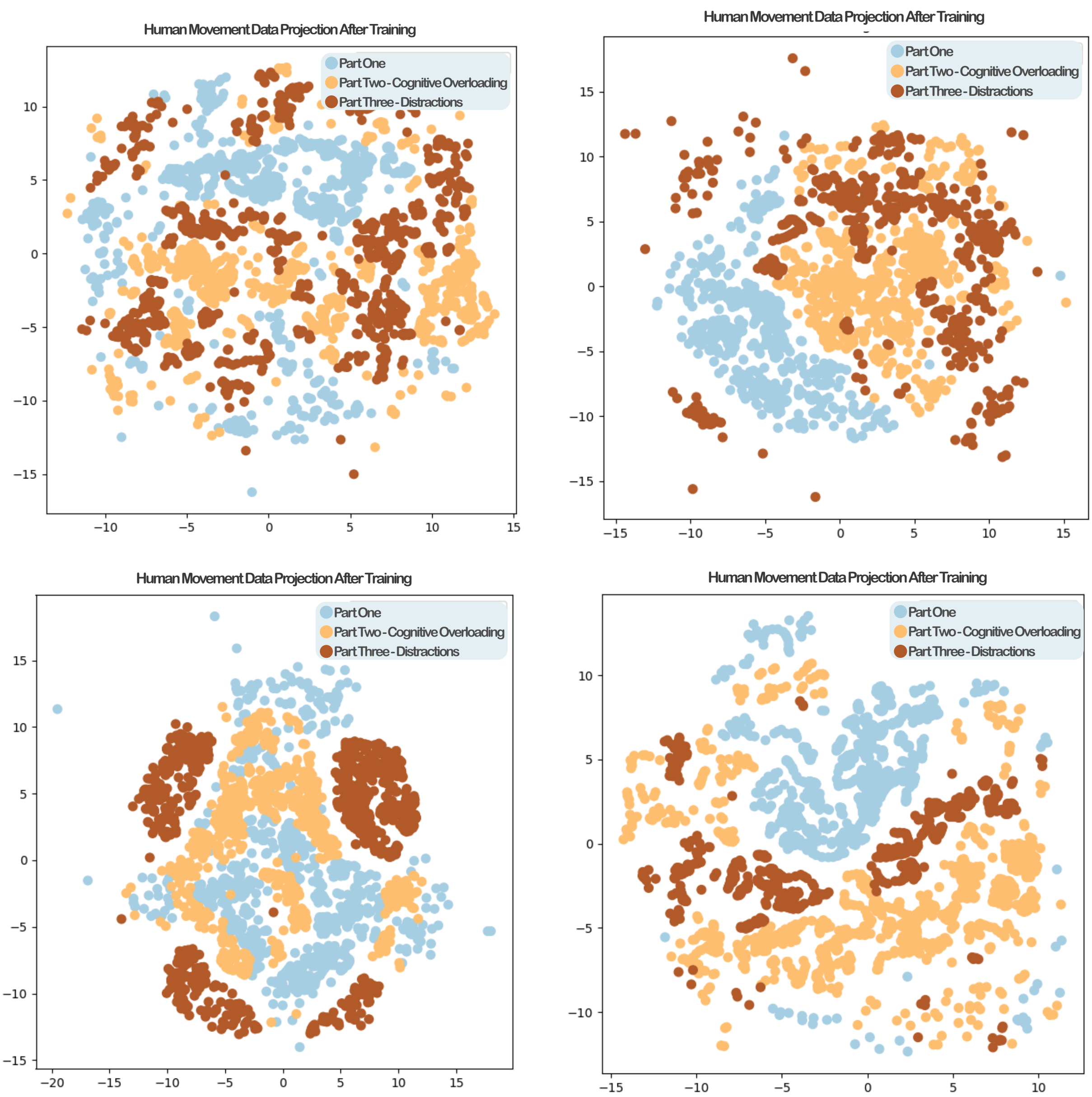


Figure 6.3: An Latent Variable Model of cooperative and non-cooperative movement created from the human and robot movement dataset based on features explained in section 6.1.3.1. The feature spaces represent the movements of four participants using GP-LVM representation.

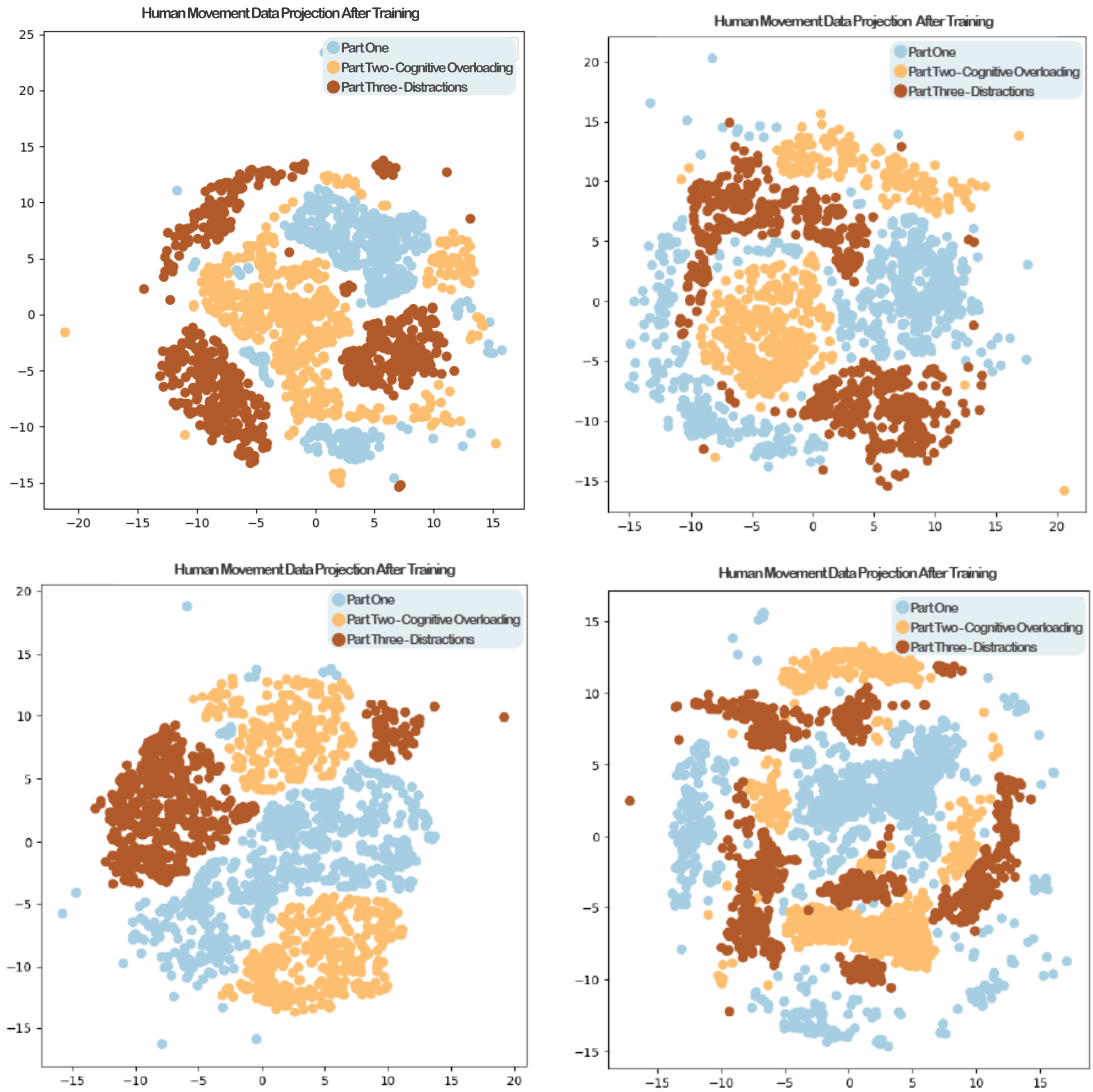


Figure 6.4: An Latent Variable Model of cooperative and non-cooperative movement created from the human and robot movement dataset based on features explained in section 6.1.3.1. The feature spaces represent the movements of four participants using GP-LVM representation.

Figure 6.5 is a measure of relative synchronicity between the robot and the human arm. The four sub-figures (A, B, C and D), show a lower measure for a more synchronous movement between the robot and the participants. In sub-figure 6.5 A, the biggest lack of synchronicity is found in the middle box-plots associated with *Part Two* of the experiment. These low synchronicity measures (highest divergence) can be seen in all the middle box-plots of each sub-figure in 6.5. The box-plots of *Part Three* (the third column in sub-figure 6.5 A) shows an average of a more synchronous movement when compared to the first column showing movement from *Part One*. This suggests that participants over time are improving their ability to have an automated plan of performing the task as mentioned in Sections 2.3.2 and 4.2.2. The high variance in the third column of sub-figure 6.5A is due to the *distractions* in *Part Three*. Similarly, this can also be seen in sub-figure 6.5B and sub-figure 6.5D. On the other hand, the third column in sub-figure 6.5C, shows the most synchronous movement out of all the 12 sets of plots. This is because the participant performing the collaborative task did not have any dressing failures in *Part Three* of the experiment whilst already having the experience of performing more than 20 dressing iterations in *Part One* and *Part Two*.

These results suggest that the representation of $f(\mathcal{T}_R, \mathcal{T}_H)$ in the form of KL divergence can be applied as part of the policy ϕ_{cm}. Additionally, the current state of interaction in the assistive task can also be derived from the measure between these deviations in movement. This current state would be equivalent to lack of collaboration when a high KL divergence is recorded when it is also used as a similarity measure.

6.3 General Discussion

6.3.1 Findings

In this chapter, we have presented a way forward of how to tackle the challenges highlighted in Chapter 4 and Chapter 5 for physical safety in physical aHRI. The previous results showed the significance of having a 'collaboration' measure for capturing the correlations between human-robot movement in an assistive task.

A good 'collaboration' measure should identify the level of collaboration between the human and the robot in the task. This measure quantifies how synchronous the movement is and infers collaboration between the human and the robot through the movement. The dataset created and used in this study allows us to compare an ideally learned skill to changes that impact the attention of the human that can hinder safety,

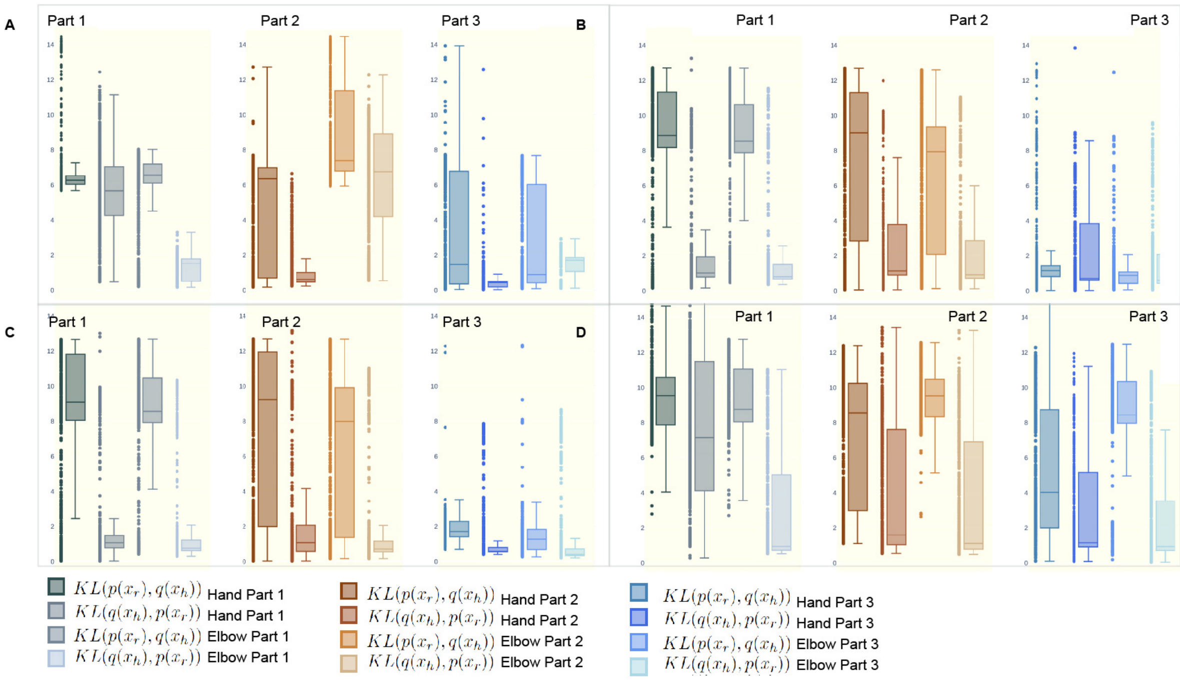


Figure 6.5: KL divergence is presented as a measure of deviation between the robot end-effector and the hand (first two box plots in each subplot) and elbow of four participants in the assistive task.

particularly in long-term movement prediction for close-proximity assistive tasks. The possibility for future work was presented through two approaches. Firstly, we showed that differences in collaborative state of the human through movement can be captured by a projection on a latent space. The features extracted from the dataset enable us to distinguish between the iterations in the experiment where the participants were cognitively overloaded and distracted to when they weren't. The projection on the latent space can be further developed to represent a function that captures the state-action pairing of these instances. By utilizing the latent space as a representation of the underlying dynamics and patterns in the data, it becomes possible to model the relationship between the states and corresponding actions. This function can then be used to guide decision-making and control in the context of physically aHRI such as CS2. Secondly, the similarity measure between the robot end-effector and human arm movement again showed higher variations during the part of experiment, which consisted of cognitive overloading and distractions. Consequently, we showed the deviation in the pattern of movement for the same participants during the different iterations. The in-between participant comparison shows that an already learnt skill of collaboration can be affected by these unexpected events. Based on these arguments the **RQ6** is satisfied. The results indicate that human movement, both in collaborative and non-collaborative states, can be utilized as prior knowledge to enhance safety precautions in physically assistive tasks. By incorporating information about collaboration and considering the impact of disturbances, the use of human movement as an input modality provides a means to ensure physical safety and improve the efficiency of human-robot interactions.

Creating such policy ϕ_{cm} would provide prior knowledge on what type of coupled human-robot movement is performed, based on the level of attention of the user. The collaboration measure can also be used as part of a method that modulates the robot movement primitive, which is based on a coupling term derived from the collaboration measure energy function.

Overall, the results show that the KL divergence manages to capture a higher variance in the movements when cognitive overloading takes place. Some of the participants adapt well to the learned skill so that the distraction in Part Three does not lead to any failure in the dressing task. This aspect of learning over time, how to synchronise movement with that of the robot, is shown in the third subplot for each participant. The participant's improvement of skill over time with the robot trajectory can be mostly seen on the KL box plots of the top right and bottom left where the KL similarity measure scores are the lowest in the last part of the experiment while still having Part two depicting the highest variance due to cognitive overloading.

6.3.2 Limitations

Despite our results showing that human movement can be used to infer collaboration states as prior knowledge, further work is still needed to fully develop and test the policy ϕ_{cm} by using either utilizes the latent space model as an energy function or employs the KL divergence measure.

6.3.3 Summary

This chapter has addressed the ultimate objective of this thesis, which is to use human movement as an input modality that can infer knowledge about the collaboration state in a complex physically aHRI.

The dataset from CS2 was used to perform further feature extraction on the human movement data. The methodology applied involved using statistical methods to uncover more fidgety and shaky movement during cognitive overloading and distraction. The purpose was to demonstrate that human behaviour is indeed affected in these instances and that this is also reflected in their movement.

The first approach implemented was the GP-LVM, which revealed that collaborative and non-collaborative movements can be distinguished in a space based on the HS. This showed the feasibility of creating a personalized space for each participant to tailor their future interactions with assistive robots. Through the integration of such findings in a policy function, a measure of the willingness to collaborate or state of collaboration can be valued based on the observed state-action of the interaction. Additionally, the second approach utilized similarity measures, specifically KL divergence, to quantify the synchronization between the human arm and the robot's end-effector. As future work, it is essential to validate this approach by additional studies and evaluations.

These results, together with the other chapter, contribute to addressing the research gaps of state-of-the art by evaluating: (i) the same input modality safety requirements in different interaction complexities and, (ii) the risk associated with changing human state and factors, (iii) through methodologies based on experimental designs that allow data collecting in real-world contexts and (iv) feedback from caring professionals.

Chapter 7

Conclusions and Future Work

The overall objective of this work was to demonstrate the importance of ensuring the safety of physically assistive human-robot interaction (aHRI) through a comprehensive evaluation of an input modality. This evaluation was conducted by examining the impact of changing environmental factors, as well as human state HS and human factors HF, on the interaction. The connotation of the work presented in this thesis extends to both scientific and societal domains. From a societal perspective, designing assistive robots can help alleviate the burden on the care sector, particularly in light of ageing populations. By collaborating with care professionals, our aim is to work towards increasing the effectiveness of designing physically assistive robots and aligning our efforts with the needs of care professionals. From a scientific perspective, we propose a collaboration measure from human movement, that can provided added safety to complex physically assistive tasks. This measure aims to address the existing research gaps identified in the state of the art by evaluating: (i) the same input modality safety requirements in different interaction complexities (ii) and the risk associated with changing human state and factors, (iii) through experimental designs that allow data collecting in real-world contexts (iv) and feedback from caring professionals.

To achieve this objective, valuable insights and feedback were gathered from care professionals, which served as inspiration for the development of the proposed collaboration measure. In Chapter 6, the human movement dataset from CS2 was utilized to extract relevant features that distinguish between the collaborative and non-collaborative states of the human. This measure of the state was deemed crucial, as highlighted in Chapter 4, where the potential failures resulting from distractions in the surrounding environment were discussed. It was concluded that while human movement prediction can effectively anticipate different movements even with slight variations (Chapter 3), ensuring physical safety through human movement is heavily influenced by the complexities of the interaction. The importance of such a measure was even reinforced in OS3, which exposed major issues in hazard analysis when it comes to assistive robots (see Chapter 5

Each chapter of this thesis focuses on addressing a set of specific research questions aimed at making a contribution to the gaps in the literature. In the next section, the most relevant findings from each chapter are summarised, aiming to address the more general research questions presented in Chapter 1 (see Section 7.1). Next, a discussion of the main limitations and the possible directions for future work (see Section 7.2). Furthermore, given that the target end-users for such robotics systems are older adults, ethical aspects are briefly discussed following the opinion obtained from OS3 in Chapter 5 (see Section 7.3). Finally the chapter is concluded by stating the main achievements and key contributions of the thesis (see Section 7.4).

7.1 Requirements for using Human Movement to design Safe Physically Assistive Human-Robot Interaction

Based on various reviews and methodologies discussed in Chapter 2, the requirements for ensuring physical safety were outlined based on the levels of complexities initially explained in Section 2.1.2.1. A set of research questions were formulated to assess the extent to which physical safety could be ensured in different interaction complexities. The case studies presented in this thesis address the various levels of complexities (see Figure 2.2). The proposed research questions aimed to verify the taxonomies presented in 2.1.2.1, which suggested that when the task of the humans heavily intersects with those of the robots, the collective interaction becomes highly dependent on the unknown environmental conditions, directly affecting the output decision function in the interaction [108]. These claims are supported by other works that argue against approaches in aHRI that do not consider unknown environmental conditions and eventually hinder the full deployability of cHRI [18, 63, 72, 111, 142]. By defining the universal function D in these taxonomies as dependent on physical safety, we evaluate the impact of human movement as input modalities in different levels of collaboration and how output decision $F(.)$. The taxonomies for each case study are:

[**RQ1, RQ2**] ← **CS1 :** $\{T_h\} \ominus \{T_r\} = \{T\}$ **and** $D = F(R)E(k) + F(H)E(.)$
[**RQ3, RQ6, RQ7**] ← **CS2 :** $\{T_r\} \cap \{T_h\} \neq \emptyset$ **and** $D = F(R,H)E(.)$**.**
[**RQ4, RQ5**] ← **OS3 :** $\{T_{r_{carer}}\} \cap \{T_h\} \neq \emptyset$ **and** $D = F(R_{carer},H)E(.)$

RQ1: In a socially assistive robot interaction context, is human movement prediction enough to guarantee physical safety?

This research question investigates to what extent human movement prediction can provide information about the collaboration intent of the human and keep physical safety. The taxonomy describing the level of complexities here indicates that physical safety can be independent of the unknown conditions in the environment. In the context of a socially assistive robot, variations in the human movement are hand related and therefore, a reaching action is to be predicted as per these sub-research questions:

RQ1a: What is the most appropriate methodology to predict human reaching movements such that variations within the same reaching goal can be represented and still distinguished between different reaching goals?

RQ1b: Can the human reaching movement be represented in the form of prior knowledge?

RQ1c: Can the human reaching movement prior knowledge be generalised over different humans?

RQ2: In a socially assistive robot interaction context, does the state-action pairing for safe robot manipulation need to change when the collaborative state of the human changes?

A set of sub-research questions to address if the assistive robot can decide on the human's physical safety based only on the known environmental factors.

RQ2a: What is the smallest time window possible that allows a high-accuracy prediction of the human reaching movement? Is it small enough to guarantee safety?

RQ2b: Can this human-reaching movement prediction guarantee the same degree of physical safety when changing the context from a socially to a physically assistive robot?

The results obtained from the collected dataset in case study CS1 provide strong evidence that human movement prediction using appropriate parameters in the ProMPs can achieve high accuracy. By utilizing prior knowledge about human reaching movement within the socially aHRI framework, the trained ProMPs enable the robot to differentiate between very close reaching targets even before the human physically touches the target cell. This capability enhances the robot's ability to anticipate and respond to human intentions.

Furthermore, the results demonstrate that even subtle variations in human movement can be detected, even when the reaching goal differs by as little as 8cm. The accuracy of the prediction extends up to 16cm on the cognitive game board when only a small initial part of the executed trajectory is observed. This means that the assistive robot can approach as close as 16cm while still monitoring the user, allowing it to provide effective guidance and assistance during the cognitive game. Importantly, these findings generalize across multiple participants, indicating the robustness of the approach.

The observed trajectories in the dataset consisted of approximately 50 time samples recorded by the Xsens suit at a frequency of 50Hz. This means that a trajectory observation of 10% corresponds to around 100ms. Based on the results, it is clear that the correct region on the board can be predicted within 100ms of the older adult changing hand posture and moving toward the board. The actual target cell can be predicted within the first 450ms, allowing the robot to accurately determine the closest 8cm where the reaching movement will end. This demonstrates that within a very short time frame of 100ms, the robot can acquire knowledge about the user's intention through the modality of human movement prediction.

However, it is important to note that the guarantee of physical safety within this time window of 450ms depends on the specific context of the aHRI. In the presented case study, CS1, physical safety from the socially assistive robot can be ensured up to 16cm away from the human's arm reach. This safety requirement is based on the proximity to the common workspace, which is the cognitive board game. However, in the context of a physically assistive robot where the robot's workspace is the human body itself, the adequacy of this 450ms time window for ensuring physical safety needs further analysis. Therefore, while the answer to **RQ2a** is affirmative, addressing **RQ2b** necessitates additional investigation and examination. Furthermore, the above findings indicate that the taxonomy in this interaction complexity can be valid since physical safety can be maintained irrespective of the unknown environmental conditions that can affect the HS, and HF

After analysing physical safety in the complexity levels of CS1, in CS2, the complexity levels are increased, and once again, the taxonomy at this level is tested through the research questions. In CS2, it was important to create an unknown environment and analyse if human behaviour is affected. Ultimately, the goal is to demonstrate that if human behaviour is affected, physical safety would depend on the robot making decisions based on this knowledge. Provided these claims are valid, it is necessary to transmit this knowledge through the modality of human movement. From CS2, it was observed that the synchronisation of human movement with the robot is hindered. These findings suggest that predicting human movement without the knowledge of the human's collaborative state can impact physical safety. With CS2, there is evidence highlighting the significance of environmental factors, HS and HF consideration in ensuring physical safety. Additionally, the qualitative human movement data shows that such knowledge can be seen through the input modality to provide knowledge about the human's collaborative state. These arguments are explored further in the final chapter of this thesis. The research questions to these findings were:

RQ3: In a physically assistive robot interaction context, can human behaviour impact their physical safety?

- **RQ3a:** Can disturbances in a dynamic environment lead to unusual variations in human movement and, therefore a failed collaboration task?
- **RQ3b:** Can prediction of human movement still guarantee safety during such known disturbances?
- **RQ3c:** In such context, can the state-action pairing remain non-adaptive to guarantee safety during such disturbances?
- **RQ3d:** Can some humans become familiar with some of the disturbances in the environment?

RQ3e: Can movement synchronization fail even though the human learned how to adapt and collaborate in the task?

RQ4: Can collaboration intent be gauged from the variations in human movement and guarantee physical safety from a more complex state-action pairing?

This question investigates if variations in human movement due to disturbance in the environment indicate an intent to the collaborate the human during the physical interaction.

The main contribution of CS2 is the analysis and quantification of disrupted human movements during a physical human-robot interaction task. The effects of these disruptions were further confirmed through qualitative evaluations of the user experience. The timeline (see Figure 4.1) and temporal layout (see Figure 4.2) of the HRI experiment devised for this study show how by using the literature on human behaviour, action cognition and motor control, the effect of unknown environments can be tested. The findings from these results and the possibility to evaluate input modalities in these contexts show how such approach can be extremely useful for other researchers conducting similar studies and for the goal of having fully deployable physically assistive robots.

The results obtained from the NASA and PeRDITA questionnaire provides additional validation for HRI experiment. The occurrence of dressing failures and mistakes (see Figure 4.4), as well as the qualitative feedback from the participants, align with the quantitative data collected on human motion data. These findings address **RQ3a**, as they demonstrate that the dynamic nature of cognitive overloading and distractions leads to atypical variations in human movement, which ultimately lead to unsuccessful dressing tasks. *Parts Two* and *Three* of the experiment were specifically designed to disrupt the way participants initially learned to perform the collaborative task. The findings depicted in Figures 4.7 and 4.8 indicate that the *cognitive overloading* in *Part Two* can result in overwhelming intrinsic cognitive load and significant extrinsic cognitive loads. However, in *Part Three* of the experiment, the recorded data shows slightly less movement than in *Part Two*, suggesting that participants were able to handle the new environmental information slightly better on their second attempt. Despite the participants learning how to collaborate in *Part One*, the occurrence of unexpected events consistently posed challenges to the germane load during the experiment, thereby validating the taxonomy at this level of complexity. The NASA showing a higher temporal demand in *Part Three* is also associated with an unknown environmental context since participants were still trying to understand the dynamics of the collaboration and build their own approach to performing the task. From the PeRDITA results, participants show uncertainty in describing the **Collaboration** as *adaptive* showing an impression of failed adaption since the synchronicity was not as present as in *Part One* during *cognitive overloading*. All participants either made a mistake or a dressing failure during the *cognitive overloading*. The participants who did not fail in the dressing task answered most questions incorrectly during the *cognitive overloading*. These findings that answer **RQ3d** were due to the fact participants were able to become familiar with the assistive task despite the cognitive distraction, but this cannot guarantee physical safety if new distractions are encountered in the future, emphasizing the ongoing potential for safety risks in physically aHRI. Furthermore, the results provide compelling evidence that even when participants had become familiar with the task, their concentration was still susceptible to disruption when unexpected events occurred. This loss of concentration led to a breakdown in interaction synchronicity. These findings directly address research question **RQ3e**, demonstrating that despite participants having sufficient time to familiarize themselves with the assistive task, they still struggled to adapt and collaborate effectively in *Part Two* and *Part Three*. While the successful completion of tasks in *Part One* indicated the presence of movement synchronization, it cannot be guaranteed that the HS remains synchronized with the robot when environmental factors come into play. These results effectively validate hypotheses H1 and H2, confirming that the collaborative task was significantly affected by variations in human movement, resulting in a loss of synchronization between the human and the robot and ultimately leading to a non-collaborative state.

The failures and mistakes in *Part Two* and *Three* can be attributed to changes in the participants' collaborative state. By analyzing the projection of human movement onto the latent space, we gain insights into the learning process throughout all three parts of the experiment. Despite encountering only minimal dressing failures in *Part One*, there is a wider dispersion of points in the latent space, indicating that participants were still in the process of mastering the task execution. The germane cognitive load, which involves constructing a mental model of the task, was likely high in *Part One*, as participants were still in the early stages of developing their mental models. This learning process is reflected in the significant variance of temporal effort, as measured by the NASA questionnaire (see Figure 4.7).

The high temporal effort observed in the experiment indicates that participants were actively learning and synchronizing their movements with the robot. The projections in *Part Two* and *Part Three* reveal that disrupted movements deviate from the centre of the 2D latent space, unlike non-disrupted movements. This suggests that imbalanced cognitive loads, as experienced in *Part Two* and *Part Three*, hinder the retrieval of task knowledge, thus affecting human motor control. The 2D latent space projections capture various types of movements, including those performed during the learning phase, movements in synchronicity with the robot, and movements disrupted by unexpected events. Addressing **RQ3b**, the findings highlight that participants' cognitive load is susceptible to influence, challenging assumptions made by approaches like CPCI and prediction methodologies that solely consider optimal human movement for ensuring physical safety. The results emphasize that human movement cannot always be presumed to be consistently collaborative, indicating a negative answer to **RQ3b**. Therefore, approaches like CPCI and prediction methodologies observed in literature cannot assume physical safety when their prior knowledge only includes optimal behaviour of human movement. This corroborates the answer provided in Chapter 3 regarding **RQ2b**, that human movement prediction alone cannot guarantee sufficient physical safety without monitoring the participants' cognitive load. An assistive robot cannot continue to adapt when the older adult is not interested or willing to collaborate.

In a context like CS2, the projections on the 2D latent space suggest the need for a more complex state-action pairing to ensure physical safety. Some projections represent human movement during the collaborative state, while others do not. These findings indicate that the answer to **RQ3c** is no, and mapping the latent space of human movement to robot actions is necessary when the human is not in a collaborative state. The state-action pairing should only remain non-adaptive in instances where the human behaviour is optimal. Considering that assistive interactions often involve older adults, ensuring physical safety requires a shift from adaptation to re-establishing a collaborative behaviour before proceeding with task adaptation. The need for such a requirement is also emphasised in Chapter 5. Conducting research to evaluate assistive robots in such contexts prior to deployment can provide valuable knowledge about which human movements are intended for collaboration and which are not. Latent space analyses, such as the one conducted in this experiment, can assist in differentiating between different parts of the experiment. These arguments partially address **RQ4**. Furthermore, Chapter 6 extends the answer to this research question by exploring methods for creating complex state-action pairings that measure collaboration through human movement.

Furthermore, personalisation is crucial for accommodating the unique collaborative states of each participant. The user experience and mistakes highlighted in the results section demonstrate that individuals can react differently to external disturbances. The complex nature of cognitive overloading and distraction's impact on human motor control underscores the need for personalisation tailored to the specific end-user. The necessity for personalisation, as revealed in Chapter 4, is further emphasized by the insights provided by the caring professional in the subsequent Chapter 5.

Based on the lessons learnt (see Section 4.4.2), CS2, proceeds on to validate the complexity level taxonomy of physically aHRI that requires CPCI. These findings support the notion that in order to maintain physical safety, it is essential to somehow measure the collaborative state of the human through the input modalities of the robot. The taxonomy of CS2 and OS3 are identical; however, in the context of OS3 the carer replaces the robot and is able to guarantee a safe and effective physically aHRI. To evaluate how carers handle these high levels of complexity and measure the user's collaborative state, the following questions were posed:

RQ5: What are the requirements for physically assistive robots to deliver physically assistive tasks?

In order to properly answer this research question, the following sub-research questions are posed to carers in care-homes:

RQ5a: How do carers physically assist older people in order to guarantee physical safety?

RQ5b: What do carers think the requirements and guidelines for physically assistive tools or robots should be?

RQ5c: Do carers think physical safety can be guaranteed by only looking at the optimal behaviour of humans?

In this OS3, conducted with caring and nursing professionals in a real-context environment, the aim was to identify the requirements and conduct a hazards analysis related to physically assisting older adults. The integration of HF, HS and environmental factors highlighted in previous chapters become evident through this study, providing valuable insights for future directions.

The use of physical assistive robots holds great potential in supporting the ageing population with various impairments and needs. However, the safety analysis techniques currently employed often overlook the complexities arising from patients' specific requirements and behaviours. As shown through OS3 in Chapter 5, these model-based safety analyses primarily focus on the robot's ability to detect or avoid hazards, but they fail to capture the complexity inherent in these tasks. The limitations of current safety metrics, reliability assessments, and human models become apparent, highlighting the need for more comprehensive metrics that consider the human element in HRI. By addressing these limitations, this argument and the findings from the observational study contribute to answering **RQ5a** and **RQ5b** shedding light on the shortcomings of current approaches to physically assistive robots.

Considering patients' diverse needs and behaviours and analyzing how they interact with assistive technology in real-world environments reveals additional hazards. Evaluation by nursing and care professionals uncovers use cases that are often overlooked by standard methods. Assistive robots would require adaptation and additional sensing capabilities to address these hazards. The current regulations offer only a superficial assessment of physical assistive interaction with robotic systems, rendering model-based safety analysis techniques inadequate without incorporating user adaptation. The feedback and insights from care professionals emphasize the importance of evaluating the human-in-the-loop aspects of interaction and technical design. By including these aspects and leveraging the expertise of professionals to define requirements, the research on physical assistive robots can be made safer. These arguments further contribute to answering **RQ5b**.

A key finding from the hazards and requirements identified in this study is that carers consistently assess the state of older adults, never assuming optimal behavior even within a single day. The dynamic nature of older adults' capabilities and behaviour necessitates continuous evaluation and adaptation by carers. This emphasizes the importance of recognizing and responding to individuals' current conditions and needs rather than relying on assumptions or generalizations. These findings directly address **RQ5c**, demonstrating that carers understand the dynamic nature of older adults and continually assess their state and needs when providing physical assistance. These findings align with the answer provided to **RQ2b**, which was discussed in Chapter 3 and Chapter 4, highlighting the importance of considering contextual factors in providing physical assistance and conducting meticulous hazard analysis for safe task execution, particularly in close proximity interactions.

Carers emphasize the importance of considering the contextual factors in the environment when providing physical assistance, as these factors continuously change and require meticulous hazard analysis to ensure safe task execution, particularly in close proximity interactions. One recurring concept from this observational study is that carers always strive to engage and measure collaboration while assisting older adults, regardless of their degree of vulnerability. Collaboration plays a critical role in determining safety in physically assistive tasks, and while evaluating it can be challenging, quantifying collaboration can serve as a key safety measure. The next chapter (Chapter6) focuses on developing a methodological approach to quantify collaboration in human-robot experiments tailored to the specific tasks, such as CS2. By conducting more realistic experiments and leveraging different modalities, this measure of collaboration can be inferred and constructed. Chapter 6 aims to make use of the taxonomy at the higher levels of complexity and base robot actions with knowledge about the HS in the unknown environmental factors not avoid hindering the physical safety.

Incorporating these insights into future studies will not only contribute to a better understanding of user experience during human-robot interaction but also advance research in safety. To ensure the safe deployment of assistive robots, it is crucial to carefully consider the input and feedback from nursing and care professionals who possess experiential knowledge in these tasks. Adopting a co-design approach that involves their expertise and incorporates their insights will help address the complexities involved and shape the development of technology in this field. Based on these arguments and findings, we aim to assess whether we can quantify collaboration from human movement as an input modality. The following research questions were posed to explore this topic:

RQ6: Following from RQ4 and RQ5, how can such prior knowledge be used to couple the human movement and robot's motion planning to guarantee safety in the context of disturbance?

- **RQ6a:** How can the variations in human movement be modelled as prior knowledge?
- **RQ6b:** Can a measure of collaboration be created from this prior knowledge to indicate a lack of synchronisation and hence a possible failure in the interaction?

RQ7 Ultimately can such collaboration measure be embedded and modelled in the robot's motion planning?

In Chapter 6, we present a way forward for addressing the challenges highlighted in Chapter 4 and Chapter 5 regarding physical safety in physical aHRI. While answering the previous research questions, arguments lead to the importance of having a 'collaboration' measure that captures the correlations between human-robot movement in an assistive task.

As per the requirements from Chapter 5, a reliable 'collaboration' measure should accurately assess the level of collaboration between the human and the robot during the task. It should quantify the synchronicity of their movements and infer the degree of collaboration based on these movements. The dataset created and utilized in CS2 enables us to compare an ideally learned skill with changes that impact the attention of the human, which can potentially hinder safety, especially in long-term movement prediction for close-proximity assistive tasks. In Chapter 6, two potential approaches were presented as a means for comparing the collaboration knowledge within the human movement dataset.

Firstly, we demonstrated that the deviation in human movement could be captured by projecting it onto a latent space. By extracting features from the dataset, we can differentiate between iterations where participants were cognitively overloaded and distracted from those where they were not. This latent space projection can be further developed to represent a function that captures the state-action pairing in these instances. By utilizing the latent space as a representation of the underlying dynamics and patterns in the data, we can model the relationship between states and corresponding actions. This function can then guide decision-making and control in physically aHRI contexts such as CS2.

Secondly, the similarity measure between the robot end-effector and human arm movement revealed higher variations during the experiment's cognitive overloading and distraction phases. Consequently, we observed deviations in the movement patterns of the same participants across different iterations. Comparisons between participants showed that even an already learned collaboration skill could be affected by unexpected events. Based on these findings and arguments, **RQ6** is satisfied. The results indicate that human movement can be utilized as prior knowledge to enhance safety precautions in physically assistive tasks in both collaborative and non-collaborative states. By incorporating information about collaboration and considering the impact of disturbances, using human movement as an input modality provides a means to ensure physical safety and improve the efficiency of human-robot interactions. Our results demonstrate that the KL divergence effectively captures higher movement variance during cognitive overloading. While some participants adapt well to the learned skill, ensuring that distractions in *Part Three* do not lead to failures in the dressing task, others show improvements in synchronizing their movements with the robot trajectory over time. These aspects of skill acquisition and improvement can be observed in the KL box plots, with lower scores indicating improved synchronization in the last part of the experiment, while *Part Two* still depicts the highest variance due to cognitive overloading.

Creating a policy ϕ_{cm} based on these insights would provide prior knowledge about the type of coupled human-robot movement performed, taking into account the user's attention level. The collaboration measure can also be integrated into a method that modulates the robot's movement primitive, incorporating a coupling term derived from the collaboration measure's cost function. In previous literature, latent spaces have been utilized to encode information about different human motions and movements. The dataset from CS2 demonstrated that if a learning phase is conducted together with the carer, the assistive robot can gather information about the collaborative and non-collaborative states of the human. These states should be verified by the carers and then provided to the assistive robot to create a personalized approach for the assistive task. The results shown in Chapter 6 indicate that the learn latent spaces can now hold knowledge about the collaborative state and be applied to robot motion planning as shown in [61, 74, 98, 152]. Additionally, the similarity measure obtained in Chapter 6 can offer valuable insights for model-based learning approaches, such as the work by Englert et al. [46]. While Englert et al. utilize probabilistic trajectory matching to adapt the robot, their method does not consider estimating collaboration. In contrast, CS2 and the results presented in Chapter 6 demonstrate that KL divergence can effectively estimate collaboration at specific instances. Therefore, instead of solely aiming to minimize KL divergence for trajectory matching purposes, it can be leveraged as a measure of collaboration, providing a more comprehensive understanding of the human-robot interaction.

7.2 Limitations, Open Challenges and Future Work

An open challenge and a limitation in our research is to consider acquiring human movement data through a camera instead of relying solely on the Xsens suit. While the Xsens suit has served our purpose of analyzing human movement in different interaction complexities, it may not be practical or feasible for every older adult to wear such a suit and undergo calibration. While significant progress has been made in 3D human joint tracking from 2D cameras, there are still challenges to overcome when it comes to tasks involving occlusion and real-context environments such as care homes. Additionally, It is also worth noting that in recent literature there are other methods that are you to predict human movement [38, 39, 135] .

A limitation with respect to the collaborative measure is the need for a framework. The proposed measure of collaboration can be further evaluated in different robotic frameworks, and its principles apply to various other input modalities. In recent literature, new physical interaction frameworks utilize latent space as prior knowledge derived to influence actions. These findings suggest that the approach taken in Chapter 6 and the methodology for creating the collaboration measure can be integrated into similar frameworks. In this thesis, our focus was on analyzing human behaviour within complex interaction contexts and identifying safety measures that would enable safer physical interactions through the evaluation of human movement. Ultimately, we wanted to analyse if collaboration and non-collaborative instances can be identified through the input modality of human movement. While we thoroughly analysed human movement and its impact on physical safety, we acknowledge that a comprehensive framework incorporating robotic factors would provide a more holistic understanding. Such a framework could include the evaluation of input modalities, the influence of changing environmental factors, and the assessment of the human state and human factors as feedback to the robot. By analyzing these measures within a complete framework, we could better understand the interplay between different elements and their impact on overall safety in physically aHRI. This comprehensive analysis would enhance the validity and applicability of our findings and provide a more robust basis for designing and implementing safety measures in real-world scenarios. Recognizing this limitation, future research should strive to develop and employ a comprehensive framework that considers all relevant factors and provides a more thorough evaluation of safety measures in physically assistive interactions. This would contribute to advancing the field and ensuring the effectiveness and reliability of physically assistive robots in various contexts and settings.

The human movement prediction methodology adopted in Chapter 3 could have been further analyzed and compared to different methodologies. However, the scope of the chapter was to determine whether human movement methodologies can differentiate between very close-reaching targets and if this can be achieved through the appropriate consideration of time and space within the context of socially aHRI. The comparison of such methodologies is a future task that can be extrapolated from the dataset of CS1.

7.2.1 Discovered Research Gaps

Several research gaps were originally specified in Chapter 2 and were addressed through the original research questions. However, some gaps in the research were discovered when the case studies were evaluated.

Firstly, there is a lack of hazard analysis and safety standards specifically concerning physically assistive robots. While there is an ageing population and a growing demand for assistive tasks, there is still a need for a proactive approach to addressing the safety aspects of physically assistive robots. The analysis of information from OS3 revealed that the current safety standards are insufficient in identifying more than half of the risks faced by older adults when using assistive technology. This significant shortcoming highlights the need for a more inclusive approach involving various professionals' expertise in developing comprehensive solutions.

Secondly, the limitations arising from assumptions about optimal human behaviour can impact methodologies in physically assistive human-robot interaction (aHRI). From CS2 and OS3, it became evident that safety risks can easily arise due to the dynamic environment in which assistive tasks are likely to occur. Many human movement prediction and robot adaptation algorithms are tested solely within laboratory environments without considering real-world scenarios. While directly involving end-users and the environments in which the technology is intended to be used can expose major shortcomings, it can also guide research in the right direction.

Finally, there is a need to plan the temporal layout of experiments carefully. The knowledge gained from the literature regarding the mental models of humans and their collaborative behaviour enabled us to test the case study's hypotheses through the appropriate experimental methodology design. This consideration highlights the importance of properly structuring experiments to capture relevant data and validate the proposed measures effectively. To our knowledge, literature does not highlight the need for accessing physical safety in assistive tasks through the approaches provided in CS2.

7.3 Ethical Aspects

With the increasing demand for caregivers in care homes, researchers are exploring the use of robots to assist with repetitive non-ergonomic tasks. However, it is crucial to recognize that certain tasks require precision, dexterity, flexibility, and cognitive decision-making, which may currently be lacking in robots. While assistive tasks aim to fulfil specific needs, it is important to ensure that the robot's cognitive capabilities align with the requirements for safeguarding the physical safety of older adults. Without sufficient cognitive decision-making abilities, physically assistive robots may not be able to ensure the safety of individuals effectively. This ethical consideration underscores the need for a thorough assessment of the capabilities and limitations of assistive robots. It highlights the importance of understanding the tasks that can be safely and effectively carried out by robots and those that still require human intervention or more advanced robotic capabilities. Addressing this ethical implication requires ongoing research and development in robotics, with a focus on enhancing the cognitive abilities of assistive robots. It also calls for collaboration among researchers, care providers, and policymakers to establish clear guidelines and regulations regarding the use of robots in care homes. This collaborative effort aims to ensure the well-being and safety of older adults while maintaining a human-centred approach to care.

Another ethical implication of relying on assistive tools or robots for older adults is the potential impact on their emotional well-being. The use of physically assistive robots in tasks raises questions about loneliness and emotional attachment. Increased dependence on robots may lead to feelings of isolation and loneliness, as human interaction and companionship are fundamental human needs. Individuals may also develop emotional attachments to these robots, considering them companions or even forming emotional bonds with them.

These aspects require attention and consideration from governments and institutions. It is crucial to address the potential consequences of increased reliance on robots for older adults and develop strategies to mitigate any negative impacts. This may involve incorporating social interaction and companionship elements into the design and deployment of assistive robots, ensuring that they are not solely seen as functional tools but also as facilitators of human connection and well-being.

Indeed, an ethical threshold is necessary when considering the cognitive and physical abilities of older adults in relation to the capabilities of assistive robots. It is important to assess whether the robot's assistance aligns with the cognitive and physical abilities of the individual and that the older adults' needs are dignifiedly considered. This assessment involves considering factors such as the complexity of the task, the individual's capacity to understand and interact with the robot, and the potential risks associated with the interaction.

The cognitive ability threshold determines whether the older adult can effectively engage with and comprehend the robot's instructions or assistance. This assessment ensures that the individual can make informed decisions, understand the limitations of the robot, and maintain control over the assistance provided. Similarly, the physical ability threshold considers whether the older adult is physically capable of safely interacting with the assistive robot in a given task. It evaluates whether the individual possesses the necessary strength, coordination, and mobility to engage with the robot without putting themselves at risk of harm.

By establishing these ethical thresholds, we can ensure that assistive robots are appropriate and safe for older adults. It helps strike a balance between the capabilities of the individual and the capabilities of the robot, ensuring that the interaction is beneficial and promotes the well-being of the older adult.

7.4 Key Contributions

The work was done with the aim of developing a collaborative measure for physical aHRI and CPCI. The work done to achieve this goal results in several contributions to the field of physically assistive robotics and HRI in general. This work contributes to the field of physically assistive robots by combining knowledge from various domains such as mental models, human behaviour, human state, human factors, and environmental factors. Integrating these factors with AI techniques used in robotic frameworks enables a comprehensive understanding of the complex interaction between humans and robots. This approach provides a way for developing more effective and context-aware physically assistive robots.

From this interdisciplinary approach toward the various factors, the main contributions are as follows:

- Human reaching movement dataset collected from 30 participants in the context of a socially aHRI (Chapter 3).

- Human reaching movement prediction methodology based on probabilistic approach as a means of physical safety in the context of socially aHRI (Chapter 3).

- Design of an experimental HRI methodology with timed interruptions to expose changes in the collaborative interaction during a physically aHRI dressing task (Chapter 4, [29]).

- Qualitative evaluation of the user experience showing how *cognitive overloading* and *distractions* increased the cognitive workload in physically aHRI (Chapter 4, [29]).
- Quantitative analysis of human movement to evaluate the collaborative behavior change during unexpected events in robot-assisted dressing task (Chapter 4, [29]).
- A focus group from professional carers on how to use various interaction modalities to acquire, maintain, and provide safe assistive tasks while aware of the safety hazards in the surrounding context (Chapter 5, [31]).
- A comparison of safety hazard analysis with respect to the requirements specified by the professional carers (Chapter 5, [31]).
- A synchronicity measure between collaborative and non-collaborative human movement (Chapter 6, [31],[28]).
- A latent space that projects human movement in a collaborative and non-collaborative state (Chapter6, [31],[28]).

APPENDIX

A

APPENDIX A

A.1 CS1 Ethical Approval and Additional Sheets/Forms

The ethical forms and sheets used for **CS1** are presented in this section. These documents were required in Spanish since experiments were carried out as part of secondment at *Institut de Robotica i Informatica Industrial* (IRI) in Barcelona, Spain.

A.1.1 CS1 Ethical Form Application

SOLICITUD DE EVALUACIÓN BIOÉTICA/BIOSEGURIDAD

(Investigación con participación de seres humanos / OMGs / Agentes biológicos de riesgo)

Cumplimentar los datos relativos a la investigación cuya evaluación ética se solicita, así como los referentes al investigador/es principal/es. Se deben señalar, marcando el correspondiente recuadro (A/B/C), las implicaciones éticas de la investigación propuesta y, en función de ello, cumplimentar las cuestiones formuladas en los apartados A, B y/o C. Se deberá adjuntar la documentación justificativa*.

(* Si en el momento de remitir la solicitud de evaluación aún no se dispone de alguno de los documentos, provisionalmente se deberá acreditar la tramitación de su obtención)

DATOS DE LA INVESTIGACIÓN	
Título	Predicción de la intención de movimiento en el contexto de una interacción robot-humano cognitiva asistencial
Proyecto (convocatoria)/ contrato/convenio/ actividad no financiada	SOCRATES (Social Cognitive Robotics in the European Society) European Union's Horizon 2020 research and innovation programme Marie Skłodowska-Curie Action
Nº Referencia	MSCA-ITN-2016-721619

DATOS DE LOS INVESTIGADOR RESPONSABLE/S		
	Investigador principal	**Investigadora responsable**
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☒ **A. Investigación con la participación de SERES HUMANOS, el manejo de sus muestras y/o datos que requieren protección**

☐ **B. Investigación con ORGANISMOS MODIFICADOS GENÉTICAMENTE (OMGs)**

☐ **C. Investigación con AGENTES BIOLÓGICOS de riesgo para humanos, animales, plantas y/o medio ambiente**

A | INVESTIGACIÓN CON LA PARTICIPACIÓN DE SERES HUMANOS, EL MANEJO DE SUS MUESTRAS Y/O DATOS QUE REQUIEREN PROTECCIÓN

Cumplimentar la siguiente información y adjuntar la documentación justificativa* requerida.

INFORMACIÓN	LOCALIZACIÓN EN LA MEMORIA (página/apartado)
Procedencia de los sujetos, muestras y/o datos procedentes de población humana (institución sanitaria, biobanco, otras entidades colaboradoras, repositorio CSIC, …)	
Estudiantes del instituto del CSIC y de la Universidad Politécnica de Catalunya. Siempre que sea posible, se intentará que el personal participante no tenga relación con el grupo que propone el experimento.	

comitedeetica@csic.es

C/ Serrano 117
28006 Madrid ESPAÑA
Telf.: 915681494
915681554

Perfil y características de los voluntarios, muestras y/o datos a utilizar (motivar su idoneidad)	Páginas 14-15 WP5 ESR12

Los experimentos se realizarán con individuos sanos de cualquier edad entre 18 y 65 años. Quedarán excluidas personas con movilidad reducida, o con discapacidad cognitiva, que pueda afectar a sus habilidades de percepción sobre el comportamiento del robot.

Los datos que se obtendrán relativos al movimiento de usuarios serán anónimos, y en ningún momento se harán grabaciones de vídeo ni fotografías. Únicamente, se registrará y almacenará la posición del brazo del usuario en el tiempo.

El usuario rellenará un cuestionario anonimizado del cual se obtendrán datos estadísticos y opiniones anónimas sobre el sistema robótico e interacción con él.

Objetivos de la investigación propuesta y motivación de la participación de seres humanos, utilización de muestras y/o datos	Páginas 14-15 WP5 ESR12

El objetivo principal es evaluar los movimientos de alcance de los usuarios para establecer medidas de seguridad. Es importante ser capaz de predecir la intención del movimiento del usuario en un espacio de trabajo compartido con el robot para así permitir una navegación segura del robot. Esta predicción también permitirá un comportamiento anticipado del robot durante el proceso de interacción con el humano.

Protocolos, fases y duración del procedimiento experimental (describir la metodología)	

Los experimentos se realizarán en el IRI a partir de un juego de mesa. No se pedirá a los participantes que completen el juego entero, sino que solo se utilizará el tablero de juego para registrar los "movimientos de selección" que realice el usuario con él. En este experimento, los participantes serán registrados recogiendo fichas de cada casilla del tablero de juego, el cual está compuesto por 20 casillas. Cada movimiento a una misma casilla del tablero se repetirá 30 veces. En algunas ocasiones, se requerirá que el usuario haga "movimientos intermedios" a alguna de las otras casillas del tablero partiendo de otra casilla. Esto nos permitirá tener un conjunto de datos en el que se puede modelar la predicción de alcance en función de la varianza de todos los movimientos recogidos de estos participantes.

Un movimiento de selección es un movimiento desde una posición de descanso a una de las casillas. La posición de descanso puede ser que el usuario coloque la mano al final de la mesa, en el reposabrazos de la silla o en su regazo. Un movimiento intermedio es un movimiento que tiene lugar después del movimiento de selección para colocarse en una de las otras casillas del tablero.

La metodología para recopilar datos de los movimientos del usuario será mediante el uso de una cámara simple. No se almacenará ninguna grabación de video ni fotografía para las personas que realizan los experimentos. Solo se almacenará los parámetros de la posición del brazo en cada instante en el espacio de trabajo. Como validación cruzada, también se utilizará un sistema de captura de movimientos (traje X-Sens) con el cual se recopilarán datos del movimiento. Esto requerirá que los participantes se pongan el traje en la parte superior del cuerpo, de manera que se coloquen un conjunto de tres sensores en el brazo para así registrar los movimientos al recoger y colocar fichas del tablero que realiza el usuario.

Nº total de sujetos, muestras y/o datos. Justificación estadística del diseño de experimentos y tamaño muestral en función de los parámetros principales	

Es importante destacar que todos los experimentos se realizarán con individuos sanos de cualquier edad entre 16 y 80 años. Registramos las características de la posición del brazo del usuario en cada instante durante el movimiento de recoger y colocar fichas del tablero, y el usuario tiene que repetir cada movimiento a cada casilla 30 veces. El estudio incluye la recopilación de información sobre la edad y el género de los participantes.

Se harán experimentos con hasta 30 personas diferentes. El tamaño de la muestra variará con cada participante ya que el tiempo de completar el movimiento puede ser diferente para cada participante.

Medidas adoptadas para salvaguardar la confidencialidad de los datos recogidos	

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La única información personal que se recogerá de cada participante es su sexo y franja de edad para tratamiento. Su nombre y contacto se pedirá sólo para gestionar su consentimiento, pero no tendrá uso científico. La información sobre los datos de cada participante será almacenada y anonimizada, de manera que no exista posibilidad de relacionar los datos con la persona. Sólo el investigador que realiza el experimento y su supervisor tendrán acceso a estos datos.	
Utilización previa y/o posterior de las muestras y/o datos. Condiciones de conservación	
El uso de los datos por otros investigadores requerirá la aprobación escrita del supervisor (correo electrónico). Los resultados que se publicarán en forma de artículo científico serán anónimos.	
Métodos alternativos a los contemplados en la experimentación	
Personal implicado: Personal experimentador, investigadores clínicos, responsable de repositorios de muestras, etc.	
Investigador principal (Guillem Alenyà) e investigadora responsable (Antonella Camilleri).	

*** Documentación justificativa:**

- Si la investigación se realiza en un centro ajeno al CSIC: Informe favorable del Comité de Ética de la Investigación (CEI) del propio centro o el del centro colaborador
- Si la investigación se realiza en un centro/instituto del CSIC utilizando muestras y/o datos facilitados por alguna institución sanitaria y/o biobanco: CEI de la entidad donante, o del comité de ética del biobanco. Si el origen de las muestras fuera distinto, informe favorable del órgano responsable correspondiente.
- Si la interacción con los voluntarios se realiza en un centro/instituto del CSIC: Informe favorable del CEI de una entidad sanitaria colaboradora o, en su defecto, documento rubricado por el facultativo designado para la supervisión del bienestar de los sujetos, acompañado este último de la Hoja de información y del documento de consentimiento informado.
- Si en la interacción con los voluntarios no se prevé daño físico o psíquico alguno: Hoja de información y documento de consentimiento informado.
- Si se van a utilizar muestras biológicas de naturaleza embrionaria, o se van a realizar técnicas en cuya virtud se obtengan células troncales: Informe favorable de la Comisión de Garantías para la Donación y Utilización de Células y Tejidos Humanos adscrita al Instituto de Salud Carlos III (ISCIII)
- Si la investigación se va a desarrollar en el marco de un estudio clínico: Informe favorable del Comité de Ética de la Investigación con medicamentos (CEIm) y, siempre que proceda, autorización de la Agencia Española de Medicamentos y Productos Sanitarios (AEMPS)

B | INVESTIGACIÓN CON ORGANISMOS MODIFICADOS GENÉTICAMENTE (OMGs)

Cumplimentar la siguiente información y adjuntar la documentación justificativa* requerida.

INFORMACIÓN	LOCALIZACIÓN EN LA MEMORIA
Centro en el que se desarrollará la investigación con OMGs	
Naturaleza, clasificación (tipo 1, 2, 3, 4) y características de los OMGs a emplear (motivar su idoneidad)	
Descripción de la/s actividad/es con OMGs (protocolo/metodología)	

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Instalaciones que se utilizarán -laboratorio, invernadero, animalario, …- (características, nivel de contención, etc.). Identificar la notificación de autorización de instalaciones y/o actividades de utilización confinada (A/ES/…/…), liberación (B/ES/../..) y comercialización (C/ES/../..)	
Destino final de los OMGs (mantenimiento, eliminación, liberación, etc.)	

*** Documentación justificativa:**

- Resolución favorable de la autoridad competente (MAPAMA/CCAA) para las instalaciones y/o actividades contempladas en la investigación propuesta.
- Alternativamente, informe favorable emitido por el órgano con competencias en materia de bioseguridad del instituto o centro donde se vaya a realizar la actividad o, en su defecto, por el Director del mismo, donde queden explícitamente identificados los datos de la resolución que autoriza las instalaciones y/o actividades de utilización confinada, liberación y/o comercialización y, como mínimo, el número de notificación de la autorización.

C | INVESTIGACIÓN CON AGENTES BIOLÓGICOS DE RIESGO PARA HUMANOS, ANIMALES, PLANTAS Y/O MEDIO AMBIENTE

Cumplimentar la siguiente información y adjuntar la documentación justificativa* requerida.

INFORMACIÓN	LOCALIZACIÓN EN LA MEMORIA
Centro en el que se va a realizar la investigación con agentes biológicos de riesgo	
Naturaleza, clasificación y características de los agentes biológicos de riesgo a emplear (motivar su idoneidad)	
Descripción del protocolo/metodología de la investigación con agentes biológicos de riesgo	
Medidas de bioseguridad. **Instalaciones a utilizar (características, nivel de contención, …)**	
Destino final de los agentes biológicos de riesgo. Otras consideraciones de bioseguridad	

*** Documentación justificativa:**

- Informe emitido por el órgano con competencias en materia de bioseguridad del instituto o centro donde se vaya a realizar la actividad o, en su defecto, por su Director, en el que conste formalmente la idoneidad de las instalaciones (comunicación, autorización INSSBT/CCAA, etc.)

En Barcelona, 10 de octubre de 2019

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[redacted]

Investigador principal
Firmado: Guillem Alenyà Ribas

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Investigadora supervisora
Firmado: Antonella Camilleri

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A.1.2 CS1 Participants Information Sheet

HOJA DE INFORMACIÓN AL PARTICIPANTE

TÍTULO DEL ESTUDIO:	**Predicción de la intención de movimiento en el contexto de una interacción robot-humano cognitiva asistencial**
TÍTULO DEL PROYECTO:	SOCRATES – *Social Cognitive Robotics in The European Society*
TIPO DE PROYECTO Y ENTIDAD PROMOTORA/FINANCIADORA:	MSCA-ITN-2016 – *Innovative Training Networks*, financiado por la Comisión Europea mediante el acuerdo de subvención nº 721619
INVESTIGADOR PRINCIPAL:	Guillem Alenyà Ribas
INVESTIGADOR/ES RESPONSABLE/S:	Antonella Camilleri
CENTRO DE ADSCRIPCIÓN:	University of the West of England, Bristol (UK)
LUGAR DONDE SE REALIZARÁ EL ESTUDIO:	Instituto de Robótica e Informática Industrial, CSIC-UPC
TELÉFONO:	93 401 1901
E-MAIL:	galenya@iri.upc.edu, Antonella.Camilleri@uwe.ac.uk

(1) INTRODUCCIÓN Y PROCEDIMIENTOS

Nos dirigimos a usted mediante este documento para informarle sobre un estudio de investigación aprobado por el Comité de Ética del CSIC, en el que se le invita a participar de forma voluntaria. Para ello le rogamos que lea esta hoja informativa con atención y nos consulte cualquier mínima duda al respecto.

Descripción de la actividad

- **Objetivos:**
  Esta investigación se lleva a cabo en el marco del proyecto SOCRATES, Innovative Training Networks, financiado por la CE mediante el acuerdo de subvención nº 721619.

  Su objetivo es el de evaluar varios aspectos de la interacción entre un usuario y un robot, cuando éste último actúa como tutor en un escenario de juegos de mesa. Más concretamente, el estudio se centra en los diferentes movimientos de alcance (movimientos del brazo derecho) que el usuario realiza para alcanzar las diferentes fichas en el tablero.

  El juego consiste en clasificar las "n" fichas colocadas aleatoriamente en un tablero. El usuario no tiene información previa excepto el número de fichas para ordenar. El propósito general es tener un robot que asista al usuario proporcionándole diferentes niveles de soporte: animándole, sugiriéndole un subconjunto de posibles soluciones, sugiriéndole la solución y eventualmente como último recurso proporcionándole la ficha correcta para moverse. La asistencia puede prestarse utilizando el habla y/o los gestos.

  El objetivo principal de este experimento es evaluar los movimientos de alcance que realizan los usuarios, de manera que podamos ser capaces de predecir la intención del movimiento de alcance del usuario en un espacio de trabajo compartido con el robot, garantizando una navegación segura del mismo.

  Es importante destacar que todos los experimentos se realizarán con individuos sanos de cualquier edad entre 18 y 65 años. Registramos el movimiento del usuario para recoger y colocar fichas del tablero. El usuario tiene que repetir cada movimiento 30 veces. El estudio incluye la recopilación de información sobre la edad y el género de los participantes. En total, se prevé hacer experimentos con hasta 30 usuarios diferentes.

- **Metodología de investigación:**

Los experimentos se realizarán en el IRI. No se pedirá a los participantes que completen el juego entero, sino que solo se utilizará el tablero de juego para registrar los "movimientos de selección" que realice el usuario con él. La recopilación de datos se utilizará en otro experimento posterior, para la integración en un marco utilizando el robot.

Los participantes serán registrados cogiendo fichas de cada casilla (espacio amarillo) del tablero mostrado en la figura 1. Este movimiento a una misma casilla del tablero se repetirá 30 veces. En algunas ocasiones, se requerirá que el usuario haga "movimientos intermedios" hacia una casilla partiendo de otra casilla diferente del tablero. Esto nos permitirá tener un conjunto de datos en el que se puede modelar la predicción de alcance en función de la varianza de todos los movimientos recogidos de estos participantes.

Un movimiento de selección es un movimiento desde una posición de descanso a una de las casillas. La posición de descanso puede ser que el usuario coloque la mano al final de la mesa, en el reposabrazos de la silla o en su regazo. Un movimiento intermedio es un movimiento que tiene lugar después del movimiento de selección para colocarse en una de las otras casillas del tablero.

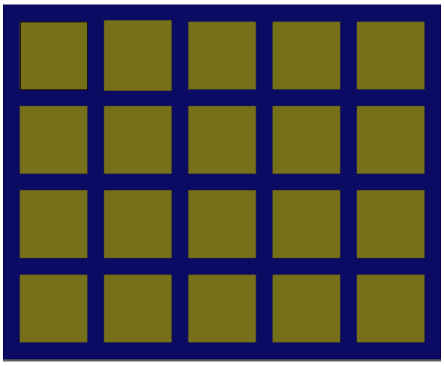

Figura 1 - Ejemplo de tablero

La metodología para recopilar datos de los movimientos del usuario será mediante el uso de una cámara simple. No se almacenará ninguna grabación de video para las personas que realizan los experimentos. Solo se almacenará la posición del brazo en cada referencia temporal. Como validación cruzada, también se utilizará un sistema de captura de movimientos (traje *X-Sens*) para recopilar datos sobre el movimiento. Esto requeriría que los participantes usen un traje especial en la parte superior del cuerpo y con el que se envolverá un conjunto de tres sensores en el brazo del usuario para registrar los movimientos al recoger y colocar fichas del tablero.

(2) NATURALEZA DE LA PARTICIPACIÓN

Su participación en este estudio es totalmente voluntaria. Usted puede decidir participar o no en este proyecto. De igual modo puede abandonar el estudio en cualquier momento revocando el consentimiento informado sin que esto le afecte de ningún modo. Usted tiene la posibilidad de elegir el destino de sus datos en caso de retirarse del estudio, incluyendo su destrucción.

Beneficios

El participante en este estudio podrá conocer la investigación que se lleva a cabo en nuestro centro sobre robótica social.

Riesgos

Los riesgos de seguridad son mínimos. No se utilizará ningún robot para esta recopilación de datos.

Diseminación de los resultados

La única información personal que se recogerá de cada participante es su sexo y su franja de edad para tratamiento estadístico. Dicha información será almacenada en los servidores del centro, y será encriptada. Sólo el investigador que realiza el experimento y su supervisor tendrán acceso a estos datos. El uso de los datos por otros investigadores requerirá la aprobación escrita del supervisor (correo electrónico). Los resultados que se publicarán en forma de artículo científico serán anónimos.

(3) PARA MÁS INFORMACIÓN

Usted tiene derecho a clarificar todas las dudas que se le presentes en cualquier momento, pudiendo solicitar información más detallada sobre la investigación. Para ello puede comunicarse con el investigador principal o el investigador responsable cuyos datos de contacto están al principio de este documento.

Si considera que todas las dudas han sido aclaradas y que tiene la convicción de participar en este estudio, a continuación, puede firmar la hoja de consentimiento informado.

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HOJA DE CONSENTIMIENTO INFORMADO

TÍTULO DEL ESTUDIO:	**Predicción de la intención de movimiento en el contexto de una interacción robot-humano cognitiva asistencial**
TÍTULO DEL PROYECTO:	SOCRATES – *Social Cognitive Robotics in The European Society*
TIPO DE PROYECTO Y ENTIDAD PROMOTORA/FINANCIADORA:	MSCA-ITN-2016 – *Innovative Training Networks*, financiado por la Comisión Europea mediante el acuerdo de subvención nº 721619
INVESTIGADOR PRINCIPAL:	Guillem Alenyà Ribas
INVESTIGADOR/ES RESPONSABLE/S:	Antonella Camilleri
CENTRO DE ADSCRIPCIÓN:	University of the West of England, Bristol (UK)
LUGAR DONDE SE REALIZARÁ EL ESTUDIO:	Instituto de Robótica e Informática Industrial, CSIC-UPC
TELÉFONO:	93 401 1901
E-MAIL:	galenya@iri.upc.edu, Antonella.Camilleri@uwe.ac.uk

Nombre del participante:
Contacto:

Título del estudio: Predicción de la intención de movimiento en el contexto de una interacción robot-humano cognitiva asistencial

DECLARO que he leído la Hoja informativa del Participante y que se me ha entregado una copia, que he tenido tiempo suficiente y se me ha dado la oportunidad de hacer preguntas.

DECLARO que todas mis preguntas sobre mi participación en este estudio de usuarios han sido respondidas satisfactoriamente.

DECLARO que entendí completamente el propósito del estudio del usuario y mi participación en él.

DECLARO que he entendido que mis datos se utilizarán para publicaciones científicas en forma seudónima y doy mi consentimiento informado para este uso.

DECLARO que entiendo que cualquier información personal que autorice proporcionar será tratada como confidencial y nunca se pondrá a disposición del público.

DECLARO además que entiendo que mi participación es voluntaria por lo que puedo retirarme de la investigación libremente, en cualquier momento y por cualquier razón, y asimismo DOY MI CONSENTIMIENTO para participar en la investigación que se me ha propuesto, únicamente bajo mi propia responsabilidad.

Firma y fecha del participante:

Declaración del investigador responsable

La información contenida en esta solicitud, incluyendo cualquier información que la acompañe, es completa y correcta. Se han intentado identificar todos los riesgos relacionados con la investigación que pueden surgir en la realización de esta investigación

Investigador principal: Guillem Alenyà
Firma y fecha:

Investigador supervisor: Antonella Camilleri
Firma y fecha:

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A.1.3 CS1 Approval of Ethical Form

INFORME DE EVALUACIÓN BIOÉTICA/BIOSEGURIDAD

Evaluados los aspectos de bioética de la investigación propuesta (Investigación con la participación de seres humanos, el manejo de sus muestras y/o datos que requieren protección) y, según los términos definidos en el proyecto, el Comité de Ética del CSIC declara que no existen objeciones que puedan constituir impedimento alguno para su desarrollo.

Para que conste a los efectos oportunos, se expide el presente informe de evaluación en Madrid, a treinta de octubre de dos mil diecinueve.

Datos del Investigador principal

Nombre	CAMILLERI, ANTONELLA (Investigadora supervisora/responsable de la actividad) ALENYÀ RIBAS, GUILLEM (Investigador principal del proyecto)
Centro / Instituto	Instituto de Robótica e Informática Industrial – IRI (Barcelona) University of the West of England (Bristol)
Teléfono	+44 117 328 6913 / 934031901
Correo electrónico	Antonella.Camilleri@uwe.ac.uk / galenya@iri.upc.edu

Datos de la Investigación propuesta

Título	Actividad de título “Predicción de la intención de movimiento en el contexto de una interacción robot-humano cognitiva asistencial”, contemplada en el proyecto de título “SOCRATES: Social cognitive robotics in the European Society”
Convocatoria	H2020-MSCA-ITN-2016
Referencia	721619

Evaluación

FAVORABLE	
Código interno: 061/2019	

CONSEJO SUPERIOR DE INVESTIGACIONES CIENTÍFICAS COMITÉ DE ÉTICA CSIC

[redacted]

Miguel García Guerrero
Presidente del Comité de Ética del CSIC

Este informe solo tiene validez para la investigación propuesta y en las condiciones en ella descritas. Cualquier cambio que afecte a las implicaciones bioéticas y/o de bioseguridad de la misma, invalida este informe y deberá ser puesto en conocimiento del Comité de Ética del CSIC para su valoración.

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A.2 CS1: Human Reaching Movement Data Analysis and Results

A.2.1 ProMPs Training Detailed Results

A.2.1.1 User 1019 Prediction for Cell 15

Prediction of User 1019 for Cell 15 at 10% observed trajectory																					
Basis Functions	**M1**	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*
	M2	*20*	*20*	*20*	*20*	*20*	*20*	*20*	*20*	*20*	*20*	*20*	*20*	*20*	*20*	*20*	*20*	*20*	*20*	*20*	20
Exp Noise		*0.01*	*0.02*	*0.03*	*0.04*	*0.05*	*0.06*	*0.07*	*0.08*	*0.09*	*0.1*	*0.11*	*0.12*	*0.13*	*0.14*	*0.15*	*0.16*	*0.17*	*0.18*	*0.19*	0.2
		3	1	4	1	3	1	1	9	9	3	3	3	3	1	9	3	1	1	1	1
		8	3	8	1	3	9	3	9	9	9	5	3	3	9	9	3	1	3	3	3
		8	3	9	8	3	9	13	13	9	9	8	8	8	9	9	3	1	3	3	9
		9	8	9	9	8	9	13	13	9	9	12	9	9	9	9	8	1	9	8	9
		9	9	9	11	9	9	13	14	9	9	13	9	9	9	12	9	5	9	9	9
		9	9	13	12	9	9	14	14	9	9	14	11	13	12	13	9	8	9	9	9
		9	9	13	13	13	13	15	15	14	12	14	13	14	13	13	9	9	13	13	13
		9	13	14	13	13	14	15	15	14	14	15	14	14	14	13	9	14	14	14	13
		9	13	15	14	14	14	15	15	15	14	15	14	15	15	15	9	14	14	14	14
		13	13	15	14	15	15	15	15	15	14	15	15	15	15	15	14	15	15	15	14
		13	14	15	14	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		13	15	15	14	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		14	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		14	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
Exact Prediction		30%	45%	60%	40%	55%	55%	70%	70%	60%	50%	65%	55%	60%	60%	60%	50%	55%	55%	55%	50%
Exact + Neighbour Cells		70%	65%	80%	65%	70%	90%	75%	90%	100%	90%	75%	75%	80%	85%	80%	80%	70%	80%	75%	80%
Correct Board Region		70%	65%	85%	65%	70%	90%	75%	90%	100%	90%	80%	75%	80%	85%	80%	80%	75%	80%	75%	80%
Middle Board Region		30%	30%	15%	15%	30%	5%	20%	10%	0%	5%	15%	20%	20%	5%	15%	20%	5%	15%	20%	15%
Incorrect Board Region		0%	5%	0%	20%	0%	5%	5%	0%	0%	5%	5%	5%	0%	10%	5%	0%	20%	5%	5%	5%

Table A.1: ProMps Training Parameters and Results for Trajectory observations of 10% for User 1019 while training for Cell 15.

Prediction of User 1019 for Cell 15 at 15% observed trajectory																					
Basis Functions	**M1**	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*
	M2	*20*	*20*	*20*	*20*	*20*	*20*	*20*	*20*	*20*	*20*	*20*	*20*	*20*	*20*	*20*	*20*	*20*	*20*	*20*	20
Exp Noise		*0.01*	*0.02*	*0.03*	*0.04*	*0.05*	*0.06*	*0.07*	*0.08*	*0.09*	*0.1*	*0.11*	*0.12*	*0.13*	*0.14*	*0.15*	*0.16*	*0.17*	*0.18*	*0.19*	0.2
		1	3	3	1	1	3	3	5	1	3	9	3	3	3	1	3	3	3	3	8
		1	3	3	8	3	3	5	8	8	5	9	3	5	3	1	5	3	8	8	9
		3	3	8	8	8	8	8	9	9	8	13	8	8	8	1	8	3	9	8	9
		9	4	11	9	9	8	8	9	9	8	14	8	8	8	8	11	5	9	8	11
		9	5	13	9	11	9	8	13	13	9	14	8	9	8	8	11	8	11	8	13
		9	8	14	9	11	13	11	14	14	9	14	8	9	9	8	13	8	11	9	14
		11	8	14	11	13	14	11	14	14	9	15	9	9	9	9	13	15	11	13	14
		11	8	14	11	14	15	14	14	14	13	15	9	9	9	9	14	15	14	13	14
		14	9	14	15	14	15	15	14	14	13	15	9	13	14	9	14	15	15	13	14
		15	9	15	15	14	15	15	14	15	14	15	11	14	14	11	14	15	15	13	14
		15	9	15	15	14	15	15	14	15	15	15	13	14	14	13	14	15	15	14	15
		15	9	15	15	15	15	15	15	15	15	15	13	15	14	14	14	15	15	14	15
		15	14	15	15	15	15	15	15	15	15	15	13	15	14	15	15	15	15	14	15
		15	14	15	15	15	15	15	15	15	15	15	14	15	15	15	15	15	15	15	15
		15	14	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	14	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
Exact Prediction		55%	20%	55%	60%	45%	65%	60%	45%	55%	50%	70%	30%	45%	35%	40%	40%	70%	60%	35%	50%
Exact + Neighbour Cells		75%	60%	75%	75%	70%	75%	65%	85%	85%	70%	95%	50%	75%	75%	60%	65%	70%	75%	55%	85%
Correct Board Region		75%	70%	75%	75%	70%	75%	70%	90%	85%	75%	95%	50%	80%	75%	60%	70%	75%	75%	55%	85%
Middle Board Region		5%	30%	20%	10%	15%	25%	20%	10%	10%	25%	5%	45%	20%	25%	20%	20%	25%	10%	45%	10%
Incorrect Board Region		20%	0%	5%	15%	15%	0%	10%	0%	5%	0%	0%	5%	0%	0%	20%	10%	0%	15%	0%	5%

Table A.2: ProMps Training Parameters and Results for Trajectory observations of 15% for User 1019 while training for Cell 15.

Prediction of User 1019 for Cell 15 at 20% observed trajectory																					
Basis Functions	**M1**	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*
	M2	*20*	*20*	*20*	*20*	*20*	*20*	*20*	*20*	*20*	*20*	*20*	*20*	*20*	*20*	*20*	*20*	*20*	*20*	*20*	20
Exp Noise		*0.01*	*0.02*	*0.03*	*0.04*	*0.05*	*0.06*	*0.07*	*0.08*	*0.09*	*0.1*	*0.11*	*0.12*	*0.13*	*0.14*	*0.15*	*0.16*	*0.17*	*0.18*	*0.19*	0.2
		1	2	1	2	1	8	3	5	1	1	1	1	5	5	1	5	3	3	1	8
		13	11	2	3	1	9	3	5	1	3	2	8	8	8	8	6	3	8	3	8
		13	13	3	5	1	9	8	5	2	5	3	8	8	8	9	6	8	8	5	11
		14	13	8	5	2	13	8	8	3	8	3	8	8	11	9	8	13	8	6	13
		14	14	8	6	3	14	8	9	9	8	3	8	9	13	13	9	13	9	8	15
		14	14	11	8	5	14	13	9	14	9	5	9	11	13	14	13	13	13	13	15
		15	14	11	11	11	14	13	9	14	11	9	11	11	14	14	13	14	14	13	15
		15	15	13	13	14	15	13	11	14	13	9	14	13	14	14	13	14	14	13	15
		15	15	14	13	15	15	14	13	15	13	13	14	14	15	14	15	15	15	14	15
		15	15	14	14	15	15	14	14	15	13	14	15	14	15	14	15	15	15	14	15
		15	15	14	15	15	15	14	14	15	14	15	15	14	15	15	15	15	15	14	15
		15	15	15	15	15	15	15	14	15	14	15	15	14	15	15	15	15	15	14	15
		15	15	15	15	15	15	15	14	15	15	15	15	15	15	15	15	15	15	14	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
Exact Prediction		70%	65%	45%	50%	60%	65%	45%	35%	60%	40%	50%	55%	40%	60%	50%	60%	60%	60%	35%	80%
Exact + Neighbour Cells		85%	80%	60%	55%	65%	90%	60%	70%	80%	55%	65%	70%	65%	70%	85%	65%	70%	75%	60%	80%
Correct Board Region		85%	80%	60%	65%	70%	90%	60%	85%	80%	60%	70%	70%	70%	75%	85%	70%	70%	75%	65%	80%
Middle Board Region		10%	10%	20%	20%	5%	10%	40%	10%	5%	30%	20%	20%	20%	20%	10%	20%	30%	25%	25%	15%
Incorrect Board Region		5%	10%	20%	15%	25%	0%	0%	5%	15%	10%	10%	10%	10%	5%	5%	10%	0%	0%	10%	5%

Table A.3: ProMps Training Parameters and Results for Trajectory observations of 20% for User 1019 while training for Cell 15.

Prediction of User 1019 for Cell 15 at 25% observed trajectory																					
Basis Functions	**M1**	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*
	M2	*20*	*20*	*20*	*20*	*20*	*20*	*20*	*20*	*20*	*20*	*20*	*20*	*20*	*20*	*20*	*20*	*20*	*20*	*20*	20
Exp Noise		*0.01*	*0.02*	*0.03*	*0.04*	*0.05*	*0.06*	*0.07*	*0.08*	*0.09*	*0.1*	*0.11*	*0.12*	*0.13*	*0.14*	*0.15*	*0.16*	*0.17*	*0.18*	*0.19*	0.2
		1	1	2	11	2	4	1	7	1	1	2	1	1	1	4	4	2	14	4	2
		1	4	11	11	4	5	1	10	2	4	11	10	2	11	4	5	2	14	10	2
		4	8	11	14	11	11	1	11	10	10	11	10	10	11	10	8	2	14	10	10
		11	10	11	14	14	11	2	11	11	11	14	10	11	11	11	12	11	14	11	11
		11	11	14	14	14	11	4	11	11	11	14	14	11	11	11	14	14	14	11	11
		14	11	14	14	14	14	4	11	13	11	14	14	11	11	11	14	14	14	11	11
		14	11	14	14	14	14	10	11	14	11	14	14	11	11	11	14	14	14	11	11
		14	11	14	14	14	14	11	14	14	11	14	14	14	14	11	14	14	14	14	14
		14	14	14	14	14	14	11	14	14	11	14	14	14	14	12	14	14	15	14	14
		14	14	14	14	14	14	11	14	14	14	14	14	14	14	12	14	14	15	14	14
		14	14	14	14	14	14	14	14	14	14	14	14	14	14	14	14	14	15	14	14
		14	14	14	14	14	14	14	14	14	14	14	15	14	14	14	14	14	15	14	14
		14	14	14	14	15	14	14	14	14	14	15	15	14	14	14	14	15	15	14	14
		15	14	14	15	15	14	14	14	14	14	15	15	14	14	14	14	15	15	14	14
		15	14	15	15	15	14	14	14	14	15	15	15	15	14	14	15	15	15	14	14
		15	14	15	15	15	14	14	14	14	15	15	15	15	14	15	15	15	15	14	14
		15	15	15	15	15	14	14	15	14	15	15	15	15	14	15	15	15	15	15	14
		15	15	15	15	15	15	14	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
Exact Prediction		35%	20%	30%	35%	40%	15%	10%	20%	15%	30%	40%	45%	30%	15%	25%	30%	40%	60%	20%	15%
Exact + Neighbour Cells		75%	65%	80%	90%	85%	75%	55%	70%	75%	60%	85%	95%	70%	65%	55%	80%	80%	100%	75%	70%
Correct Board Region		80%	70%	80%	90%	90%	85%	65%	70%	75%	65%	85%	95%	70%	65%	65%	90%	80%	100%	80%	70%
Middle Board Region		0%	5%	0%	0%	0%	0%	0%	0%	5%	0%	0%	0%	0%	0%	0%	5%	0%	0%	0%	0%
Incorrect Board Region		20%	25%	20%	10%	10%	15%	35%	30%	20%	35%	15%	5%	30%	35%	35%	5%	20%	0%	20%	30%

Table A.4: ProMps Training Parameters and Results for Trajectory observations of 25% for User 1019 while training for Cell 15.

Prediction of User 1019 for Cell 15 at 30% observed trajectory																					
Basis Functions	**M1**	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*
	M2	*20*	*20*	*20*	*20*	*20*	*20*	*20*	*20*	*20*	*20*	*20*	*20*	*20*	*20*	*20*	*20*	*20*	*20*	*20*	20
Exp Noise		*0.01*	*0.02*	*0.03*	*0.04*	*0.05*	*0.06*	*0.07*	*0.08*	*0.09*	*0.1*	*0.11*	*0.12*	*0.13*	*0.14*	*0.15*	*0.16*	*0.17*	*0.18*	*0.19*	0.2
		3	3	3	2	3	2	3	8	5	2	1	2	2	3	9	3	2	2	3	2
		5	5	3	5	3	3	8	9	5	3	3	5	2	3	9	3	3	8	3	3
		9	8	8	5	9	3	9	9	9	9	9	5	5	5	9	3	8	9	5	9
		9	8	9	5	9	5	9	9	9	9	9	8	8	9	9	8	8	9	10	9
		9	9	9	9	9	8	9	9	9	9	9	8	8	9	9	9	9	9	14	9
		10	9	9	9	9	8	9	10	9	9	9	9	8	13	14	9	9	9	14	14
		13	9	9	9	9	9	9	11	9	10	9	10	8	14	14	9	13	9	14	14
		14	9	9	9	9	9	9	14	9	13	10	10	9	15	14	9	13	9	14	14
		14	9	13	14	14	9	9	14	9	14	10	14	9	15	14	9	14	9	14	14
		14	14	13	14	14	14	10	14	9	14	10	14	14	15	14	9	14	13	14	14
		14	14	14	14	14	14	14	14	10	14	14	14	14	15	14	9	14	14	14	14
		14	15	14	14	14	14	14	14	14	14	15	14	14	15	14	9	14	14	14	14
		15	15	14	14	15	14	14	15	14	14	15	14	15	15	15	9	14	14	15	14
		15	15	15	15	15	15	14	15	15	14	15	14	15	15	15	14	15	14	15	14
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	14	15	14	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	14	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
Exact Prediction		40%	45%	35%	35%	40%	35%	30%	40%	35%	30%	45%	30%	40%	65%	40%	20%	35%	25%	40%	30%
Exact + Neighbour Cells		85%	80%	75%	80%	90%	70%	90%	90%	90%	85%	90%	75%	65%	80%	100%	80%	70%	85%	85%	90%
Correct Board Region		90%	85%	75%	95%	90%	75%	90%	90%	100%	85%	90%	85%	70%	85%	100%	80%	70%	85%	90%	90%
Middle Board Region		10%	15%	25%	0%	10%	20%	10%	5%	0%	10%	5%	10%	20%	15%	0%	20%	25%	10%	10%	5%
Incorrect Board Region		0%	0%	0%	5%	0%	5%	0%	5%	0%	5%	5%	5%	10%	0%	0%	0%	5%	5%	0%	5%

Table A.5: ProMps Training Parameters and Results for Trajectory observations of 30% for User 1019 while training for Cell 15.

Prediction of User 1019 for Cell 15 at 35% observed trajectory

Basis Functions	**M1**	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*
	M2	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*
Exp Noise		*0.01*	*0.02*	*0.03*	*0.04*	*0.05*	*0.06*	*0.07*	*0.08*	*0.09*	*0.1*	*0.11*	*0.12*	*0.13*	*0.14*	*0.15*	*0.16*	*0.17*	*0.18*	*0.19*	*0.2*
		2	3	1	2	2	3	5	3	5	2	8	5	3	3	5	9	5	3	5	9
		5	3	5	9	3	5	9	3	5	3	8	5	3	5	5	9	9	5	5	9
		5	5	9	9	3	9	9	3	5	3	9	5	5	5	5	9	9	8	9	9
		9	5	9	9	9	9	9	3	5	5	9	5	5	5	5	9	9	9	9	9
		9	5	9	9	9	9	9	5	9	9	9	9	9	9	5	9	9	9	9	9
		9	5	9	9	9	9	9	5	9	9	9	9	9	9	9	9	9	9	10	9
		9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	10	9	14	9
		9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	10	9	14	9
		9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	10	14	9	14	9
		9	9	9	9	9	9	9	9	9	9	9	9	9	9	10	13	14	9	14	14
		10	9	10	9	9	9	10	10	9	9	9	9	9	14	10	14	14	9	15	14
		10	10	13	9	9	14	14	10	9	9	9	14	10	14	10	14	14	9	15	14
		14	14	14	13	10	14	14	14	9	14	9	14	14	14	10	14	14	14	15	14
		14	14	14	14	10	15	14	14	10	14	10	14	14	14	14	15	14	14	15	14
		15	15	14	14	14	15	14	14	14	15	14	14	14	14	14	15	14	14	15	14
		15	15	14	14	14	15	14	14	14	15	14	14	14	15	14	15	14	14	15	14
		15	15	15	15	14	15	15	15	15	15	15	14	15	15	15	15	14	14	15	14
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	14	14	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
Exact Prediction		30%	30%	20%	20%	15%	35%	20%	20%	20%	30%	20%	15%	20%	25%	20%	35%	10%	10%	50%	15%
Exact + Neighbour Cells		85%	70%	85%	90%	85%	90%	95%	70%	80%	80%	90%	80%	80%	80%	75%	95%	95%	85%	90%	100%
Correct Board Region		95%	90%	90%	90%	85%	95%	100%	80%	100%	85%	90%	100%	90%	95%	100%	95%	100%	90%	100%	100%
Middle Board Region		0%	10%	5%	5%	10%	5%	0%	20%	0%	10%	10%	0%	10%	5%	0%	5%	0%	10%	0%	0%
Incorrect Board Region		5%	0%	5%	5%	5%	0%	0%	0%	0%	5%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%

Table A.6: ProMps Training Parameters and Results for Trajectory observations of 35% for User 1019 while training for Cell 15.

Prediction of User 1019 for Cell 15 at 40% observed trajectory

Basis Functions	**M1**	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*
	M2	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*
Exp Noise		*0.01*	*0.02*	*0.03*	*0.04*	*0.05*	*0.06*	*0.07*	*0.08*	*0.09*	*0.1*	*0.11*	*0.12*	*0.13*	*0.14*	*0.15*	*0.16*	*0.17*	*0.18*	*0.19*	*0.2*
		3	5	5	3	5	9	3	5	3	3	3	5	5	5	4	5	3	2	5	3
		5	9	5	5	5	9	5	5	5	5	5	5	9	5	5	5	3	3	5	3
		9	9	9	5	9	9	9	9	5	9	5	5	9	5	5	5	5	5	5	5
		9	9	9	9	9	9	9	9	5	9	5	9	9	5	5	5	9	5	9	5
		9	9	9	9	9	9	9	9	5	9	5	9	9	9	5	9	9	5	9	9
		9	9	9	9	9	9	9	9	5	9	9	9	9	9	9	9	9	9	9	9
		9	9	9	9	9	9	9	9	9	9	9	9	14	9	9	9	9	9	9	9
		9	9	9	9	10	9	10	9	9	9	9	9	14	9	9	9	9	9	9	9
		9	14	9	9	14	9	10	9	9	9	9	9	14	9	9	9	10	9	9	9
		9	14	9	9	14	9	10	9	9	9	14	9	14	9	9	9	14	9	9	9
		9	14	9	14	14	10	10	9	9	9	14	9	14	10	9	9	14	10	10	10
		9	14	9	14	14	10	10	9	9	9	14	10	15	10	9	9	14	14	10	14
		10	14	9	14	14	14	14	14	14	9	14	14	15	14	10	10	14	14	14	14
		10	14	9	14	14	15	14	14	14	9	14	14	15	14	14	10	14	15	14	15
		10	15	9	14	14	15	14	14	14	10	14	14	15	14	14	14	14	15	14	15
		14	15	9	14	15	15	14	14	14	14	14	14	15	14	14	14	14	15	14	15
		14	15	14	14	15	15	14	14	14	14	15	15	15	15	14	14	14	15	14	15
		15	15	14	15	15	15	15	14	15	14	15	15	15	15	14	14	15	15	14	15
		15	15	15	15	15	15	15	14	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
Exact Prediction		15%	30%	10%	15%	25%	35%	15%	5%	15%	10%	20%	20%	45%	20%	10%	10%	15%	35%	10%	35%
Exact + Neighbour Cells		90%	95%	90%	85%	90%	100%	90%	90%	70%	90%	75%	85%	95%	80%	75%	80%	85%	75%	85%	80%
Correct Board Region		95%	100%	100%	95%	100%	100%	95%	100%	95%	95%	95%	100%	100%	100%	100%	100%	90%	90%	100%	90%
Middle Board Region		5%	0%	0%	5%	0%	0%	5%	0%	5%	5%	5%	0%	0%	0%	0%	0%	10%	5%	0%	10%
Incorrect Board Region		0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	5%	0%	0%

Table A.7: ProMps Training Parameters and Results for Trajectory observations of 40% for User 1019 while training for Cell 15.

Prediction of User 1019 for Cell 15 at 45% observed trajectory																					
Basis Functions	**M1**	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*	*32*
	M2	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*
Exp Noise		*0.01*	*0.02*	*0.03*	*0.04*	*0.05*	*0.06*	*0.07*	*0.08*	*0.09*	*0.1*	*0.11*	*0.12*	*0.13*	*0.14*	*0.15*	*0.16*	*0.17*	*0.18*	*0.19*	0.2
		5	5	5	9	5	9	5	5	3	5	5	5	5	5	5	5	3	3	3	5
		5	9	5	9	9	9	5	5	3	5	9	5	5	9	9	5	5	5	5	9
		9	9	9	9	9	9	5	9	4	5	9	5	5	9	9	5	9	5	5	9
		9	9	9	9	9	9	9	9	5	9	9	9	5	9	9	9	9	9	5	9
		9	9	9	9	9	9	9	9	9	9	9	9	5	9	10	9	9	9	5	9
		9	9	9	9	9	9	9	9	9	9	9	9	9	9	10	9	9	9	9	9
		9	9	9	9	9	10	9	9	9	9	9	10	9	9	10	9	9	9	9	9
		9	9	9	9	9	14	9	9	9	14	9	10	9	10	10	9	9	9	9	9
		9	10	9	9	10	14	10	9	9	15	10	10	9	10	14	9	9	9	9	10
		10	10	9	9	10	15	10	9	10	15	10	10	10	10	14	9	9	10	9	10
		10	10	9	9	14	15	10	9	14	15	14	10	10	14	14	9	10	10	9	10
		10	14	10	9	15	15	10	9	14	15	14	10	10	14	14	9	10	14	9	10
		10	14	14	10	15	15	10	9	14	15	14	14	14	14	15	10	14	14	10	10
		10	14	15	10	15	15	14	14	14	15	14	14	14	14	15	10	14	14	14	14
		14	14	15	10	15	15	15	14	14	15	14	15	14	14	15	10	14	14	15	15
		15	14	15	10	15	15	15	14	15	15	15	15	15	15	15	14	15	15	15	15
		15	14	15	14	15	15	15	15	15	15	15	15	15	15	15	14	15	15	15	15
		15	15	15	14	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
Exact Prediction		25%	15%	35%	10%	45%	55%	30%	20%	25%	60%	25%	30%	25%	25%	40%	15%	25%	25%	30%	30%
Exact + Neighbour Cells		90%	95%	90%	100%	95%	100%	85%	90%	80%	85%	95%	85%	75%	95%	95%	85%	90%	85%	75%	95%
Correct Board Region		100%	100%	100%	100%	100%	100%	100%	100%	90%	100%	100%	100%	100%	100%	100%	100%	95%	95%	95%	100%
Middle Board Region		0%	0%	0%	0%	0%	0%	0%	0%	10%	0%	0%	0%	0%	0%	0%	0%	5%	5%	5%	0%
Incorrect Board Region		0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%

Table A.8: ProMps Training Parameters and Results for Trajectory observations of 45% for User 1019 while training for Cell 15.

Prediction of User 1019 for Cell 15 at 50% observed trajectory																					
Basis Functions	**M1**	*31*	*31*	*31*	*31*	*31*	*31*	*31*	*31*	*31*	*31*	*31*	*31*	*31*	*31*	*31*	*31*	*31*	*31*	*31*	*31*
	M2	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*
Exp Noise		*0.01*	*0.02*	*0.03*	*0.04*	*0.05*	*0.06*	*0.07*	*0.08*	*0.09*	*0.1*	*0.11*	*0.12*	*0.13*	*0.14*	*0.15*	*0.16*	*0.17*	*0.18*	*0.19*	0.2
		4	9	5	4	5	4	5	4	5	4	9	4	4	5	4	5	5	9	4	5
		5	9	5	5	9	5	9	5	5	5	9	5	9	5	5	5	9	9	5	5
		9	9	9	9	9	5	9	5	5	5	9	5	9	9	5	5	9	9	5	5
		9	10	9	9	9	9	10	5	5	9	9	9	9	9	5	5	9	9	5	9
		9	10	9	9	9	9	10	5	9	9	9	9	9	9	9	5	9	9	5	9
		9	10	9	9	9	9	10	5	9	9	9	9	9	9	9	9	9	9	5	9
		9	10	9	9	9	9	10	9	9	9	9	9	9	9	9	9	9	9	9	9
		9	15	9	9	9	9	14	9	9	9	10	9	9	9	9	9	9	9	9	9
		9	15	9	9	9	9	14	9	9	9	10	9	9	9	10	9	10	14	9	9
		10	15	9	10	9	9	14	9	10	9	10	9	10	9	10	10	10	15	10	9
		10	15	10	10	10	9	15	9	14	10	15	10	15	9	14	10	10	15	15	9
		10	15	10	10	15	9	15	9	15	10	15	14	15	9	14	15	14	15	15	9
		10	15	15	10	15	10	15	9	15	10	15	15	15	9	15	15	15	15	15	9
		14	15	15	10	15	14	15	15	15	14	15	15	15	14	15	15	15	15	15	10
		15	15	15	14	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
Exact Prediction		30%	65%	40%	25%	45%	30%	50%	35%	45%	30%	50%	40%	50%	30%	40%	45%	40%	55%	50%	30%
Exact + Neighbour Cells		90%	100%	90%	90%	95%	85%	95%	70%	80%	85%	100%	85%	95%	90%	80%	75%	95%	100%	70%	85%
Correct Board Region		100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Middle Board Region		0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Incorrect Board Region		0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%

Table A.9: ProMps Training Parameters and Results for Trajectory observations of 50% for User 1019 while training for Cell 15.

Prediction of User 1019 for Cell 15 at 55% observed trajectory

Basis Functions M1	*31*	*31*	*31*	*31*	*31*	*31*	*31*	*31*	*31*	*31*	*31*	*31*	*31*	*31*	*31*	*31*	*31*	*31*	*31*	*31*
M2	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*
Exp Noise	*0.01*	*0.02*	*0.03*	*0.04*	*0.05*	*0.06*	*0.07*	*0.08*	*0.09*	*0.1*	*0.11*	*0.12*	*0.13*	*0.14*	*0.15*	*0.16*	*0.17*	*0.18*	*0.19*	0.2
	9	9	9	9	5	9	9	9	9	4	9	9	9	9	9	9	9	5	9	9
	9	9	9	9	9	9	9	9	9	9	9	9	10	9	9	9	9	9	9	9
	9	9	9	9	9	9	9	9	9	9	9	9	10	9	9	9	9	9	9	9
	9	9	9	9	9	9	9	10	9	9	9	9	10	9	9	9	9	9	9	9
	9	9	9	9	9	9	9	10	9	9	9	9	10	9	9	9	10	9	9	9
	9	9	10	10	9	10	9	10	9	9	10	9	15	9	9	9	10	9	10	10
	9	9	10	10	9	10	9	10	9	9	10	9	15	9	10	9	10	10	10	10
	9	10	14	10	9	10	9	10	10	9	14	10	15	10	10	9	14	10	10	14
	9	10	14	10	10	10	14	10	14	9	15	10	15	10	10	10	15	10	10	14
	10	10	15	10	10	14	14	14	14	9	15	10	15	10	10	14	15	14	10	15
	14	10	15	15	10	14	14	14	14	10	15	15	15	14	14	14	15	14	10	15
	15	14	15	15	15	15	14	14	14	10	15	15	15	15	15	14	15	15	14	15
	15	15	15	15	15	15	14	14	14	10	15	15	15	15	15	15	15	15	15	15
	15	15	15	15	15	15	15	15	14	14	15	15	15	15	15	15	15	15	15	15
	15	15	15	15	15	15	15	15	15	14	15	15	15	15	15	15	15	15	15	15
	15	15	15	15	15	15	15	15	15	14	15	15	15	15	15	15	15	15	15	15
	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
Exact Prediction	45%	40%	55%	50%	45%	45%	35%	35%	30%	20%	60%	50%	75%	45%	45%	40%	60%	45%	40%	55%
Exact + Neighbour Cells	100%	100%	100%	100%	95%	100%	100%	100%	100%	95%	100%	100%	100%	100%	100%	100%	100%	95%	100%	100%
Correct Board Region	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Middle Board Region	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Incorrect Board Region	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%

Table A.10: ProMps Training Parameters and Results for Trajectory observations of 55% for User 1019 while training for Cell 15.

Prediction of User 1019 for Cell 15 at 60% observed trajectory

Basis Functions M1	*31*	*31*	*31*	*31*	*31*	*31*	*31*	*31*	*31*	*31*	*31*	*31*	*31*	*31*	*31*	*31*	*31*	*31*	*31*	*31*
M2	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*
Exp Noise	*0.01*	*0.02*	*0.03*	*0.04*	*0.05*	*0.06*	*0.07*	*0.08*	*0.09*	*0.1*	*0.11*	*0.12*	*0.13*	*0.14*	*0.15*	*0.16*	*0.17*	*0.18*	*0.19*	0.2
	9	9	9	9	9	9	9	9	9	9	9	9	5	10	9	9	9	5	9	9
	9	10	9	9	9	9	9	9	10	9	9	9	9	10	10	9	9	9	9	10
	9	10	9	10	9	9	9	9	15	9	9	9	9	10	10	10	9	9	9	10
	9	10	9	10	10	9	9	9	15	10	9	9	9	15	10	10	9	9	9	10
	9	10	9	10	10	10	9	9	15	10	9	10	9	15	15	10	9	9	10	15
	10	15	10	10	10	10	9	10	15	10	10	10	9	15	15	10	9	9	10	15
	10	15	10	10	10	10	10	10	15	10	10	10	9	15	15	15	10	10	10	15
	10	15	14	10	15	10	10	10	15	15	10	10	10	15	15	15	10	10	10	15
	15	15	15	10	15	10	15	10	15	15	15	15	10	15	15	15	10	15	10	15
	15	15	15	15	15	15	15	15	15	15	15	15	10	15	15	15	10	15	15	15
	15	15	15	15	15	15	15	15	15	15	15	15	10	15	15	15	15	15	15	15
	15	15	15	15	15	15	15	15	15	15	15	15	10	15	15	15	15	15	15	15
	15	15	15	15	15	15	15	15	15	15	15	15	10	15	15	15	15	15	15	15
	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
Exact Prediction	60%	75%	60%	55%	65%	55%	60%	55%	90%	65%	60%	60%	35%	85%	80%	70%	50%	60%	55%	80%
Exact + Neighbour Cells	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	95%	100%	100%	100%	100%	95%	100%	100%
Correct Board Region	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Middle Board Region	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Incorrect Board Region	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%

Table A.11: ProMps Training Parameters and Results for Trajectory observations of 60% for User 1019 while training for Cell 15.

Prediction of User 1019 for Cell 15 at 65% observed trajectory																					
Basis Functions	**M1**	*31*	*31*	*31*	*31*	*31*	*31*	*31*	*31*	*31*	*31*	*31*	*31*	*31*	*31*	*31*	*31*	*31*	*31*	*31*	*31*
	M2	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*
Exp Noise		*0.01*	*0.02*	*0.03*	*0.04*	*0.05*	*0.06*	*0.07*	*0.08*	*0.09*	*0.1*	*0.11*	*0.12*	*0.13*	*0.14*	*0.15*	*0.16*	*0.17*	*0.18*	*0.19*	*0.2*
		10	9	15	9	9	9	10	10	9	10	9	9	9	9	9	10	9	10	10	9
		10	10	15	10	10	10	10	10	10	10	10	9	9	10	10	10	10	10	15	10
		10	10	15	10	10	15	10	10	10	10	10	10	9	10	10	10	10	10	15	10
		10	10	15	10	10	15	15	10	10	10	10	10	10	10	15	10	10	15	15	10
		15	10	15	10	10	15	15	15	10	15	15	15	10	10	15	10	15	15	15	15
		15	10	15	15	15	15	15	15	10	15	15	15	15	10	15	10	15	15	15	15
		15	10	15	15	15	15	15	15	10	15	15	15	15	10	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	10	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
Exact Prediction		80%	65%	100%	75%	75%	90%	85%	80%	65%	80%	80%	80%	75%	60%	85%	70%	80%	85%	95%	80%
Exact + Neighbour Cells		100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Correct Board Region		100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Middle Board Region		0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Incorrect Board Region		0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%

Table A.12: ProMps Training Parameters and Results for Trajectory observations of 65% for User 1019 while training for Cell 15.

Prediction of User 1019 for Cell 15 at 70% observed trajectory																					
Basis Functions	**M1**	*31*	*31*	*31*	*31*	*31*	*31*	*31*	*31*	*31*	*31*	*31*	*31*	*31*	*31*	*31*	*31*	*31*	*31*	*31*	*31*
	M2	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*
Exp Noise		*0.01*	*0.02*	*0.03*	*0.04*	*0.05*	*0.06*	*0.07*	*0.08*	*0.09*	*0.1*	*0.11*	*0.12*	*0.13*	*0.14*	*0.15*	*0.16*	*0.17*	*0.18*	*0.19*	*0.2*
		10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	9	10	9	9
		10	15	10	10	10	10	10	15	10	10	10	10	10	10	10	10	10	10	10	10
		14	15	10	10	10	10	10	15	10	10	15	10	15	10	10	10	10	15	10	10
		15	15	10	10	10	10	10	15	15	15	15	15	15	10	10	10	10	15	15	10
		15	15	10	10	15	15	10	15	15	15	15	15	15	10	10	10	15	15	15	10
		15	15	10	15	15	15	10	15	15	15	15	15	15	10	15	10	15	15	15	10
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	10	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
Exact Prediction		85%	95%	70%	75%	80%	80%	70%	95%	85%	85%	90%	85%	90%	70%	75%	65%	80%	90%	85%	70%
Exact + Neighbour Cells		100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Correct Board Region		100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Middle Board Region		0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Incorrect Board Region		0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%

Table A.13: ProMps Training Parameters and Results for Trajectory observations of 70% for User 1019 while training for Cell 15.

Prediction of User 1019 for Cell 15 at 75% observed trajectory																					
Basis Functions	**M1**	*29*	*29*	*29*	*29*	*29*	*29*	*29*	*29*	*29*	*29*	*29*	*29*	*29*	*29*	*29*	*29*	*29*	*29*	*29*	*29*
	M2	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*
Exp Noise		*0.01*	*0.02*	*0.03*	*0.04*	*0.05*	*0.06*	*0.07*	*0.08*	*0.09*	*0.1*	*0.11*	*0.12*	*0.13*	*0.14*	*0.15*	*0.16*	*0.17*	*0.18*	*0.19*	0.2
		9	9	9	9	15	10	10	9	9	15	9	10	9	9	9	9	9	15	15	10
		10	10	10	9	15	10	15	10	10	15	10	15	9	10	9	9	10	15	15	10
		10	10	10	10	15	10	15	10	10	15	10	15	10	10	10	15	10	15	15	10
		10	15	15	10	15	10	15	10	15	15	10	15	10	15	10	15	10	15	15	15
		10	15	15	15	15	10	15	10	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	10	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	10	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
Exact Prediction		75%	85%	85%	80%	100%	75%	95%	65%	85%	100%	80%	95%	80%	85%	80%	90%	80%	100%	100%	85%
Exact + Neighbour Cells		100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Correct Board Region		100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Middle Board Region		0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Incorrect Board Region		0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%

Table A.14: ProMps Training Parameters and Results for Trajectory observations of 75% for User 1019 while training for Cell 15.

Prediction of User 1019 for Cell 15 at 80% observed trajectory																					
Basis Functions	**M1**	*29*	*29*	*29*	*29*	*29*	*29*	*29*	*29*	*29*	*29*	*29*	*29*	*29*	*29*	*29*	*29*	*29*	*29*	*29*	*29*
	M2	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*
Exp Noise		*0.01*	*0.02*	*0.03*	*0.04*	*0.05*	*0.06*	*0.07*	*0.08*	*0.09*	*0.1*	*0.11*	*0.12*	*0.13*	*0.14*	*0.15*	*0.16*	*0.17*	*0.18*	*0.19*	0.2
		9	9	9	9	15	10	10	9	9	15	9	10	9	9	9	9	9	15	15	10
		10	10	10	9	15	10	15	10	10	15	10	15	9	10	9	9	10	15	15	10
		10	10	10	10	15	10	15	10	10	15	10	15	10	10	10	15	10	15	15	10
		10	15	15	10	15	10	15	10	15	15	10	15	10	15	10	15	10	15	15	15
		10	15	15	15	15	10	15	10	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	10	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	10	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
Exact Prediction		75%	85%	85%	80%	100%	75%	95%	65%	85%	100%	80%	95%	80%	85%	80%	90%	80%	100%	100%	85%
Exact + Neighbour Cells		100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Correct Board Region		100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Middle Board Region		0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Incorrect Board Region		0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%

Table A.15: ProMps Training Parameters and Results for Trajectory observations of 80% for User 1019 while training for Cell 15.

Prediction of User 1019 for Cell 15 at 85% observed trajectory																					
Basis Functions	**M1**	*28*	*28*	*28*	*28*	*28*	*28*	*28*	*28*	*28*	*28*	*28*	*28*	*28*	*28*	*28*	*28*	*28*	*28*	*28*	*28*
	M2	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*
Exp Noise		*0.01*	*0.02*	*0.03*	*0.04*	*0.05*	*0.06*	*0.07*	*0.08*	*0.09*	*0.1*	*0.11*	*0.12*	*0.13*	*0.14*	*0.15*	*0.16*	*0.17*	*0.18*	*0.19*	*0.2*
		10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
		10	10	10	14	14	10	10	10	10	10	15	10	10	10	10	14	10	10	10	10
		10	10	10	15	14	15	10	10	10	10	15	15	15	14	10	15	10	10	10	10
		10	14	14	15	14	15	10	10	10	15	15	15	15	14	10	15	14	10	14	10
		15	14	15	15	15	15	15	10	10	15	15	15	15	15	15	15	15	14	15	10
		15	15	15	15	15	15	15	15	14	15	15	15	15	15	15	15	15	14	15	10
		15	15	15	15	15	15	15	15	14	15	15	15	15	15	15	15	15	14	15	14
		15	15	15	15	15	15	15	15	14	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
Exact Prediction		80%	75%	80%	90%	80%	90%	80%	75%	60%	85%	95%	90%	90%	80%	80%	90%	80%	65%	80%	65%
Exact + Neighbour Cells		100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Correct Board Region		100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Middle Board Region		0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Incorrect Board Region		0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%

Table A.16: ProMps Training Parameters and Results for Trajectory observations of 85% for User 1019 while training for Cell 15.

Prediction of User 1019 for Cell 15 at 90% observed trajectory																					
Basis Functions	**M1**	*28*	*28*	*28*	*28*	*28*	*28*	*28*	*28*	*28*	*28*	*28*	*28*	*28*	*28*	*28*	*28*	*28*	*28*	*28*	*28*
	M2	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*	*18*
Exp Noise		*0.01*	*0.02*	*0.03*	*0.04*	*0.05*	*0.06*	*0.07*	*0.08*	*0.09*	*0.1*	*0.11*	*0.12*	*0.13*	*0.14*	*0.15*	*0.16*	*0.17*	*0.18*	*0.19*	*0.2*
		15	9	14	9	10	14	10	15	14	9	14	9	9	14	9	10	10	14	10	10
		15	9	15	14	10	15	14	15	15	10	14	10	10	15	10	10	14	15	14	14
		15	14	15	15	15	15	15	15	15	15	14	15	14	15	14	14	14	15	14	14
		15	14	15	15	15	15	15	15	15	15	15	15	15	15	14	14	14	15	15	14
		15	14	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	14
		15	14	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
		15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
Exact Prediction		100%	70%	95%	90%	90%	95%	90%	100%	95%	90%	85%	90%	85%	95%	80%	80%	80%	95%	85%	75%
Exact + Neighbour Cells		100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Correct Board Region		100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Middle Board Region		0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Incorrect Board Region		0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%

Table A.17: ProMps Training Parameters and Results for Trajectory observations of 90% for User 1019 while training for Cell 15.

A.2.1.2 CS1 Additional ProMps Results

10%

35 M1
20 M2

1	2	3	4	5
6	7	8	9	10
11	12	13	14	15

USER 1019 Cell 1

1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
2	1	1	1	1	2	1	2	1	1	1	1	1	1	1	1	1	1	1	2
4	1	1	1	1	4	1	2	1	2	2	1	1	1	1	1	1	1	1	5
5	1	1	1	1	4	1	2	2	2	2	1	1	2	1	1	1	1	1	5
5	1	1	1	1	4	2	5	2	4	4	2	5	2	2	1	1	1	1	5
5	1	1	4	1	5	2	5	2	5	5	2	5	5	4	2	2	2	1	5
11	1	1	5	2	5	2	5	2	5	11	2	5	5	5	2	2	2	2	6
11	5	2	5	5	5	2	5	2	11	11	4	5	5	5	2	5	4	4	11
11	5	5	11	6	5	4	11	5	11	11	11	5	5	11	4	11	5	5	11
11	5	5	11	11	11	11	11	11	11	11	11	11	5	11	4	11	5	5	11
11	5	11	11	11	11	11	11	11	11	11	11	11	11	11	6	11	5	5	11
11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	6	11	11	11	11
11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11
11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11
11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11
11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11

15%

35 M1
20 M2

1	2	3	4	5
6	7	8	9	10
11	12	13	14	15

1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2
1	1	1	1	1	1	1	1	1	1	1	1	2	1	1	1	1	1	1	4
1	1	1	1	1	1	1	1	1	1	1	2	2	2	2	1	4	1	1	4
2	1	1	1	2	1	1	1	1	1	4	4	2	4	2	1	5	1	1	5
5	1	1	2	5	1	1	1	2	1	5	4	5	4	4	1	5	1	1	5
5	2	1	5	6	4	1	1	2	1	5	5	5	4	5	4	5	2	6	5
5	2	2	5	11	5	5	1	4	1	5	5	5	5	5	5	11	2	11	11
5	5	2	5	11	5	5	2	4	2	5	5	5	5	5	5	11	5	11	11
5	5	5	5	11	5	11	2	5	5	11	11	5	5	5	11	11	11	11	11
11	5	5	5	11	5	11	4	5	6	11	11	5	9	5	11	11	11	11	11
11	11	11	6	11	11	11	5	5	11	11	11	11	11	9	11	11	11	11	11
11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11
11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11
11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11
11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11
11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11

Actual Cell 1	7	9	10	8	7	9	10	11	8	11	7	6	5	6	6	9	6	9	9	2
Neighouring Cells 6,7,3	1	2	2	2	2	0	0	2	2	2	0	1	3	1	2	0	0	2	1	3
Neighouring Cells 11,12,13,8,3	7	6	6	5	10	6	8	5	5	6	8	8	6	6	5	8	10	8	10	10
Neighouring Cells 4,9,14	0	0	0	0	0	1	0	1	2	0	1	2	0	4	2	1	1	0	0	2
Neighouring Cells 5,10,15	5	3	2	5	1	4	2	1	3	1	4	3	6	3	5	2	3	1	0	3

20%

35 M1
20 M2

1	2	3	4	5
6	7	8	9	10
11	12	13	14	15

1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1	1	1	4	1	1	1	2	1	1
1	1	1	4	1	1	1	1	1	1	1	1	1	5	1	1	1	4	1	1
1	1	2	4	1	1	1	4	2	4	2	2	2	11	1	4	1	4	1	1
2	1	4	5	2	1	2	4	2	4	4	4	5	11	1	5	1	5	1	1
2	2	4	9	4	2	4	5	4	5	5	4	5	11	2	5	1	5	5	1
2	2	5	11	5	4	5	5	4	5	5	5	5	11	5	11	1	5	5	4
4	4	5	11	5	5	5	9	5	5	5	5	5	11	5	11	2	9	5	4
4	5	5	11	5	5	5	9	5	5	5	5	5	11	5	11	2	11	5	5
5	5	11	11	5	6	5	11	5	11	11	5	11	11	5	11	4	11	5	5
5	5	11	11	5	11	5	11	11	11	11	5	11	11	5	11	5	11	11	5
5	5	11	11	11	11	11	11	11	11	11	11	11	11	5	11	5	11	11	5
11	5	11	11	11	11	11	11	11	11	11	11	11	11	5	11	11	11	11	11
11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11
11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11
11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11
11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11

Actual Cell 1	7	8	6	5	7	8	7	6	6	6	6	6	6	4	8	6	10	4	8	9
Neighouring Cells 6,7,3	3	2	1	0	1	2	1	0	2	0	1	1	1	0	1	0	2	1	0	0
Neighouring Cells 11,12,13,8,3	5	4	8	11	6	7	6	8	7	8	8	6	8	14	4	11	5	9	7	5
Neighouring Cells 4,9,14	2	1	2	3	1	1	1	4	2	2	1	2	0	1	0	1	1	3	0	2
Neighouring Cells 5,10,15	3	5	3	1	5	2	5	2	3	4	4	5	5	1	7	2	2	3	5	4

25%

35 M1
20 M2

1	2	3	4	5
6	7	8	9	10
11	12	13	14	15

1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	4	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	4	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	4	1	1	1	1
4	1	1	1	1	1	1	1	1	1	1	1	1	1	1	4	1	1	2	1
4	4	1	1	1	1	2	1	2	1	1	1	1	1	1	5	1	1	2	1
5	5	2	1	5	1	4	1	4	1	1	1	1	1	1	5	2	1	4	1
5	5	4	4	5	1	5	1	4	2	1	1	1	1	2	5	4	1	4	1
5	5	4	4	5	4	5	4	4	4	2	2	4	2	4	5	4	5	4	4
5	11	5	4	5	4	5	5	5	4	5	4	4	4	4	11	4	5	5	4
5	11	5	5	5	4	5	5	5	4	5	4	4	5	5	11	4	11	5	4
5	11	11	11	11	5	11	5	11	5	5	5	5	5	5	11	5	11	5	4
5	11	11	11	11	5	11	6	11	5	6	5	5	11	11	11	5	11	5	11
11	11	11	11	11	5	11	11	11	6	11	5	5	11	11	11	5	11	11	11
11	11	11	11	11	9	11	11	11	11	11	11	6	11	11	11	11	11	11	11
11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11
11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11
11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11
11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11

Actual Cell 1	5	6	7	8	7	9	6	9	6	8	9	9	9	9	8	2	7	9	5	9
Neighouring Cells 6,7,3	0	0	1	0	0	0	1	1	1	2	2	1	1	1	1	0	1	0	2	0
Neighouring Cells 11,12,13,8,3	6	10	8	8	8	4	8	6	8	5	6	5	4	7	7	10	5	9	6	7
Neighouring Cells 4,9,14	2	1	2	3	0	4	1	1	3	3	0	2	3	1	2	4	4	0	3	4
Neighouring Cells 5,10,15	7	3	2	1	5	3	4	3	2	2	3	3	3	2	2	4	3	2	4	0

30%

35 M1
20 M2

1	2	3	4	5
6	7	8	9	10
11	12	13	14	15

1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	4	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	4	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	4	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	5	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	5	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	5	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	6	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	11	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	11	11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
9	11	11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	11	11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	11	11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	11	11	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	11	11	11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	11	11	11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

35%

35 M1
20 M2

1	2	3	4	5
6	7	8	9	10
11	12	13	14	15

1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	4	1	1	1	1	1	1	1	1	1	1
1	1	1	4	4	1	1	1	4	4	1	4	1	1	1	1	1	1	1	1
2	1	1	4	4	1	1	4	4	4	1	4	1	1	1	1	1	2	1	1
4	2	1	4	4	1	1	4	5	4	1	4	1	2	1	1	1	5	4	2
4	4	1	4	4	4	1	4	5	5	4	4	1	4	1	1	2	5	4	4
4	4	2	4	4	4	4	4	5	5	4	4	1	4	1	1	2	5	4	4
4	4	4	4	4	4	4	4	5	5	4	5	2	5	2	1	4	5	4	4
5	5	4	5	5	5	4	4	5	5	4	5	2	5	4	2	4	11	5	4
5	5	4	6	5	5	4	5	5	5	5	5	4	5	4	2	5	11	5	4
5	5	4	6	5	11	5	5	5	5	5	5	4	5	4	4	5	11	5	5
5	5	5	11	5	11	5	5	5	5	6	11	5	11	4	5	11	11	11	5
11	5	5	11	5	11	5	5	11	5	11	11	5	11	11	11	11	11	11	5
11	5	5	11	5	11	5	6	11	5	11	11	5	11	11	11	11	11	11	5
11	5	5	11	5	11	5	11	11	5	11	11	11	11	11	11	11	11	11	11
11	6	5	11	11	11	11	11	11	5	11	11	11	11	11	11	11	11	11	11
11	11	9	11	11	11	11	11	11	5	11	11	11	11	11	11	11	11	11	11
11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11
11	11	11	11	11	11	11	11	12	11	11	11	11	11	11	11	11	11	11	11
11	11	11	12	12	11	11	12	12	11	11	11	11	11	11	12	11	12	11	11

Actual Cell 1	3	4	6	2	2	5	6	3	2	1	5	2	7	4	7	8	5	3	4	4
Neighouring Cells 6,7,3	1	2	1	2	0	0	0	1	0	0	1	0	2	1	1	2	2	1	0	1
Neighouring Cells 11,12,13,8,3	8	4	3	9	5	10	5	6	8	3	8	9	6	9	8	8	9	12	9	6
Neighouring Cells 4,9,14	4	3	5	6	6	3	4	6	2	4	4	5	2	2	4	1	2	0	4	5
Neighouring Cells 5,10,15	4	7	5	1	7	2	5	4	8	12	2	4	3	4	0	1	2	4	3	4

40%

35 M1
20 M2

1	2	3	4	5
6	7	8	9	10
11	12	13	14	15

1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1

1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	2	1	1	1	2	1	1	1	1	1	4	1	1	2
1	2	1	1	1	1	4	2	1	4	2	1	1	2	1	2	4	1	4	2
1	4	1	4	4	1	4	2	1	4	4	2	1	4	4	4	5	1	4	4
1	4	2	4	4	4	4	4	4	4	4	2	1	4	4	4	5	2	4	4
2	4	2	4	5	4	4	4	4	4	4	4	1	4	4	5	5	2	4	4
4	4	2	4	5	4	4	4	4	4	4	4	1	5	5	5	9	4	4	5
4	4	4	4	9	4	4	5	4	4	5	4	1	5	5	5	11	4	4	5
4	5	4	5	11	5	5	5	4	5	5	4	4	5	5	5	11	4	5	9
4	5	4	5	11	5	5	5	5	5	5	4	5	5	9	11	11	4	5	9
4	5	5	5	11	9	5	5	5	5	5	4	5	11	9	11	11	4	5	11
4	5	5	5	11	11	11	5	5	11	11	5	5	11	11	11	11	4	5	11
4	5	5	5	11	11	11	11	11	11	11	5	9	11	11	11	11	11	5	11
5	11	9	5	11	11	11	11	11	11	11	5	11	11	11	11	11	11	11	11
5	11	11	11	11	11	11	11	11	11	11	5	11	11	11	11	11	11	11	11
9	11	11	11	11	11	11	11	11	11	11	5	11	11	11	11	11	11	11	11
11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11
11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11
11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11

Actual Cell 1	6	3	5	4	4	5	2	3	5	3	2	4	9	3	4	3	2	5	3	2
Neighouring Cells 6,7,3	1	1	3	0	0	0	1	2	0	0	2	2	0	1	0	1	0	2	0	2
Neighouring Cells 11,12,13,8,3	3	6	5	5	11	8	8	7	7	8	8	3	6	9	8	10	12	7	6	9
Neighouring Cells 4,9,14	8	5	4	5	3	5	6	3	5	6	4	6	2	3	5	2	3	6	6	5
Neighouring Cells 5,10,15	2	5	3	6	2	2	3	5	3	3	4	5	3	4	3	4	3	0	5	2

50%

35 M1

20 M2

1	2	3	4	5
6	7	8	9	10
11	12	13	14	15

1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
1	2	4	1	1	1	1	1	1	1	4	1	1	1	1	1	2	1	4	4
1	4	4	1	1	1	1	1	1	1	4	2	1	1	1	4	4	4	4	4
2	4	4	2	1	1	1	2	1	4	4	2	1	1	1	4	4	4	4	4
4	4	4	4	1	1	1	2	4	4	4	4	4	4	1	4	4	4	4	4
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4	5	4	4	4	4	4	4	4	4	4	4	4	4	2	4	4	4	4	4
5	11	4	4	5	4	4	4	4	4	4	4	4	4	4	5	4	4	4	4
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11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11
11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11

45%

30 M1

20 M2

1	2	3	4	5
6	7	8	9	10
11	12	13	14	15

45%

30

20

1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	1
1	1	1	1	1	1	1	2	1	1	0	0	0	0	0	0	0	0	0	0	1
2	1	1	1	4	4	1	2	1	4	0	0	0	0	0	0	0	0	0	0	1
4	4	1	4	4	4	1	4	2	4	0	0	0	0	0	0	0	0	0	0	1
4	4	1	4	4	4	4	4	2	4	0	0	0	0	0	0	0	0	0	0	4

4	4	3	4	4	4	4	4	4	4	0	0	0	0	0	0	0	0	0	0	4
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6	5	5	11	6	6	11	11	11	9	0	0	0	0	0	0	0	0	0	0	11
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11	11	11	11	11	11	11	11	11	11	0	0	0	0	0	0	0	0	0	0	11
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50%

35 M1

20 M2

1	2	3	4	5
6	7	8	9	10
11	12	13	14	15

1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1	1	1	1	4	1	1	1	1	1
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4	4	1	4	2	4	4	11	4	4	4	5	4	4	5	5	4	4	5	6
5	4	4	4	2	4	4	11	5	4	4	5	4	5	6	5	4	4	5	11
9	4	4	5	4	4	4	11	5	4	4	5	4	5	9	11	4	4	9	11
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11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11
11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11

55%

35 M1

20 M2

1	2	3	4	5
6	7	8	9	10
11	12	13	14	15

1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
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6	4	11	4	4	4	4	1	4	2	4	1	4	2	4	1	4	4	4	4
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11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11

60%

35 M1

20 M2

1	2	3	4	5
6	7	8	9	10
11	12	13	14	15

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1	2	1	1	2	1	1	1	1	2	1	1	1	1	1	1	1	1	1	1
1	4	1	1	4	1	1	1	1	4	1	1	1	2	1	1	1	1	2	1
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1	4	4	4	4	4	4	4	4	11	4	9	4	4	4	4	2	4	4	4
2	6	4	4	11	4	4	4	4	11	4	11	9	4	4	11	2	4	4	4
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65%

35 M1

20 M2

1	2	3	4	5
6	7	8	9	10
11	12	13	14	15

1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
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3	1	2	2	2	1	4	2	4	4	2	4	1	1	4	1	2	1	1	4
4	1	2	4	4	2	4	4	4	4	4	4	1	1	6	1	2	1	4	4
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4	4	4	4	4	4	4	4	4	4	4	4	1	4	11	4	2	1	4	4
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6	4	4	11	11	11	11	6	6	4	6	6	2	6	11	6	11	2	4	6
6	4	4	11	11	11	11	11	6	4	6	6	4	8	11	11	11	2	4	6
9	4	4	11	11	11	11	11	11	6	11	6	4	8	11	11	11	4	9	6
9	9	4	11	11	11	11	11	11	6	11	11	4	11	11	11	11	4	11	9
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11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11
11	11	11	14	11	11	11	11	11	11	11	11	14	11	11	11	11	11	11	11

70%

35 M1

20 M2

1	2	3	4	5
6	7	8	9	10
11	12	13	14	15

1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1

1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	1	1	1
4	1	1	4	1	1	1	1	1	1	1	1	1	1	1	1	4	1	2	1
4	1	2	4	1	1	2	1	1	1	1	1	1	1	2	1	4	1	4	1
4	1	4	4	1	4	4	2	1	1	1	1	1	1	4	1	4	2	4	1
4	1	4	4	2	4	4	2	2	1	2	2	2	1	4	1	4	3	4	2
4	2	4	4	4	4	4	4	2	1	4	2	2	2	4	4	4	3	4	4
4	4	4	4	4	4	4	4	4	1	4	2	4	2	6	4	4	4	4	4
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11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11
11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11

75%

35 M1
20 M2

1	2	3	4	5
6	7	8	9	10
11	12	13	14	15

1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	4	2	1	1	1	1	1	1	1	1	1	1	1	1	1
4	1	1	1	1	4	2	2	1	1	2	3	1	1	1	1	1	2	2	1
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4	1	2	1	1	4	4	4	4	1	4	4	4	1	1	1	3	4	2	1
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80%

35 M1
20 M2

1	2	3	4	5
6	7	8	9	10
11	12	13	14	15

1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
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1	4	1	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
1	4	1	2	1	1	3	1	1	1	1	1	1	1	1	1	1	1	1	1
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1	4	1	4	1	1	4	1	2	4	1	4	1	11	1	4	4	4	1	4
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11	11	11	11	4	4	11	4	11	11	11	4	4	11	4	8	11	11	11	11
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11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11
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85%

35 M1

20 M2

1	2	3	4	5
6	7	8	9	10
11	12	13	14	15

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4	1	2	4	4	4	4	4	1	4	1	2	1	1	4	2	4	4	4	1
8	2	4	8	4	4	4	4	1	4	1	4	4	4	11	4	4	4	4	4
8	4	4	11	4	4	4	4	2	4	4	4	4	4	11	4	4	4	8	8
11	4	4	11	4	4	4	4	2	11	4	4	11	4	11	4	11	4	8	11
11	4	4	11	4	4	8	4	4	11	4	4	11	11	11	8	11	11	11	11
11	4	4	11	11	8	11	4	4	11	4	4	11	11	11	8	11	11	11	11
11	8	4	11	11	11	11	8	4	11	4	8	11	11	11	11	11	11	11	11
11	11	8	11	11	11	11	11	4	11	11	11	11	11	11	11	11	11	11	11
11	11	11	11	11	11	11	11	8	11	11	11	11	11	11	11	11	11	11	11
11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11
11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11

90%

35 M1

20 M2

1	2	3	4	5
6	7	8	9	10
11	12	13	14	15

1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	1	1	1	1
1	1	1	1	1	1	2	1	1	1	1	1	1	1	1	4	1	1	1	1
1	1	1	1	1	1	3	1	1	1	1	1	1	1	1	4	1	1	1	1
1	1	1	1	1	1	4	1	2	1	1	1	1	4	1	4	1	1	2	1
1	1	2	1	1	1	4	1	4	2	1	1	1	4	4	4	4	2	4	1
1	1	4	1	1	4	4	1	4	2	1	1	1	4	4	4	4	4	4	1
1	1	4	1	1	4	4	2	4	4	1	2	1	8	4	4	4	4	4	4
3	4	4	4	1	4	4	4	4	4	4	4	2	8	4	8	4	4	4	8
4	4	8	4	4	4	4	4	4	4	4	4	4	11	4	11	4	8	4	11
4	8	8	4	8	4	11	4	4	4	4	11	4	11	4	11	4	8	4	11
4	8	8	4	8	8	11	8	4	4	8	11	11	11	4	11	4	11	8	11
11	11	11	4	11	11	11	11	8	8	8	11	11	11	4	11	11	11	8	11
11	11	11	8	11	11	11	11	8	8	11	11	11	11	8	11	11	11	11	11
11	11	11	8	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11
11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11
11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11
11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11

A.2.1.3 CS1 Additional ProMps Results

10%

	1	2	3	4	5
35 M1	6	7	**8**	9	10
20 M2	11	12	13	14	15

User 1019 cell 8 Predicitons

1	1	4	1	2	1	1	1	1	1	1	1	1	1	1	1	4	1	1	1
1	1	4	2	2	1	1	1	2	1	1	1	1	1	1	4	5	2	1	1
2	1	4	4	2	5	1	2	2	2	1	1	1	1	1	4	7	3	1	1
2	1	5	4	4	5	2	5	4	2	1	2	2	**2**	1	5	7	4	1	4
4	2	5	5	4	5	4	5	4	2	2	4	4	**2**	1	5	8	4	2	4
5	2	5	5	5	5	4	5	4	4	2	4	4	5	1	5	9	4	2	4
5	5	5	5	5	5	5	5	4	5	4	5	4	5	2	5	10	4	4	5
5	5	5	6	5	5	5	6	5	5	4	5	5	6	4	5	10	5	5	5
10	5	5	6	5	5	5	6	5	5	5	5	10	6	5	10	11	5	5	6
10	5	9	6	5	5	5	6	5	5	5	5	11	6	5	10	11	9	5	6
10	5	10	6	6	5	5	6	5	6	5	6	11	**8**	5	10	11	9	5	9
10	5	10	6	10	6	5	9	6	7	7	10	11	11	5	11	11	10	9	9
11	5	10	7	10	10	5	11	6	9	10	11	11	11	5	11	11	10	10	10
11	11	11	10	11	11	6	11	6	10	11	11	11	11	5	11	11	11	10	11
11	11	11	10	11	11	10	11	10	10	11	11	11	11	5	11	11	11	10	11
11	11	11	10	11	11	10	11	11	11	11	11	11	**12**	6	11	11	11	11	11
11	11	11	10	11	11	11	11	11	11	11	14	11	**14**	10	11	11	11	11	11
11	11	11	11	11	11	11	11	11	14	11	14	11	**14**	11	11	12	11	11	11
14	11	11	11	11	11	11	14	11	14	14	14	13	**14**	11	13	14	12	11	14
14	11	14	14	11	15	12	14	11	14	14	14	14	**14**	14	14	14	14	11	14

Same Row	0	0	1	1	0	0	0	1	0	2	1	0	0	1	0	0	4	2	1	2
Top Row	3	2	2	3	4	0	3	1	6	4	4	3	4	2	2	2	0	6	3	3
Bottom Row	2	0	1	1	0	0	1	2	0	3	2	4	2	5	1	2	3	2	0	2
X	5	2	4	5	4	0	4	4	6	9	7	7	6	8	3	4	7	10	4	7
	15	18	15	15	15	20	16	16	14	11	13	13	14	12	17	16	12	10	16	13
	15	18	15	15	15	20	16	16	14	11	13	13	14	12	17	16	12	10	16	13
Y	20	20	19	20	19	20	20	20	20	20	20	20	20	20	20	20	19	20	20	20

15%

	1	2	3	4	5
35 M1	6	7	**8**	9	10
20 M2	11	12	13	14	15

1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	1	1

4	1	1	1	2	4	4	2	2	1	1	1	4	1	2	1	1	2	1	2
4	2	1	2	4	4	4	4	2	2	2	2	4	4	4	1	1	2	2	4
5	4	1	4	4	4	5	4	4	2	2	2	5	5	4	2	1	2	2	4
5	5	1	4	4	5	5	4	4	4	2	4	5	5	4	2	2	5	4	5
5	5	2	4	5	5	5	4	5	5	2	5	5	5	4	2	2	5	5	5
5	6	4	4	5	5	5	5	6	5	4	5	6	5	5	5	2	5	5	6
5	6	4	4	5	5	9	5	10	5	5	5	6	5	5	6	2	5	5	6
6	10	5	5	5	6	10	5	10	8	5	6	6	5	5	10	5	6	5	7
10	11	5	5	9	6	11	5	10	9	5	6	7	5	6	10	6	6	5	7
10	11	6	6	9	6	11	9	11	9	5	6	10	6	6	11	6	6	5	8
11	11	6	7	9	8	11	9	11	10	5	8	10	10	7	11	10	8	5	10
11	11	10	9	10	9	11	9	11	11	6	9	11	10	9	11	10	10	6	10
11	11	10	10	10	10	11	10	11	11	10	11	11	10	10	11	10	10	6	10
11	11	10	10	10	10	11	10	11	11	10	11	11	10	11	11	11	11	10	11
11	11	11	11	11	10	11	11	11	11	10	11	11	11	11	14	11	11	11	11
11	12	11	11	11	11	11	11	11	11	11	11	11	11	11	14	11	11	11	11
11	13	14	11	11	11	12	14	11	14	11	11	14	11	11	14	13	11	11	11
15	14	14	14	14	11	14	14	11	14	11	12	14	11	14	14	14	12	14	11

Same Row	0	0	0	2	3	2	1	3	0	3	0	2	1	0	2	0	0	1	0	3
Top Row	3	2	3	6	4	3	2	5	4	3	5	3	2	1	5	3	4	4	3	3
Bottom Row	0	3	2	1	1	0	2	2	0	2	0	1	2	0	1	4	2	1	1	0
X	3	5	5	9	8	5	5	10	4	8	5	6	5	1	8	7	6	6	4	6
	17	15	15	11	12	15	15	10	16	12	15	14	15	19	12	13	14	14	16	14
Y	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20

20%

	1	2	3	4	5
35 M1	6	7	**8**	9	10
20 M2	11	12	13	14	15

1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	1
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	2
1	4	1	4	1	1	2	1	1	1	1	1	2	2	1	1	1	1	2	2
4	4	2	4	1	4	4	2	2	2	2	1	2	2	4	1	1	1	4	4
5	5	2	4	4	4	5	4	4	2	4	2	5	2	5	2	1	1	5	5
5	5	5	5	4	5	5	5	4	4	5	2	5	4	5	2	1	1	5	5
6	6	9	5	5	5	5	5	5	4	5	9	5	4	5	5	1	2	6	6
6	6	9	5	5	5	5	5	5	4	5	10	6	5	5	6	2	4	9	8
6	6	10	5	6	9	5	5	6	5	5	10	6	5	5	8	4	4	10	9
8	6	11	5	6	10	6	10	6	5	6	11	9	6	6	8	4	5	11	11
10	9	11	5	10	11	6	10	6	5	8	11	9	9	10	9	6	5	11	11
10	9	11	6	11	11	10	10	9	9	8	11	10	9	10	10	6	5	11	11

11	10	11	6	11	11	10	10	10	10	9	11	10	**9**	11	10	8	8	11	11
11	11	11	7	11	11	11	11	11	10	10	11	11	**10**	11	11	8	10	11	11
11	11	11	10	11	11	11	11	11	11	10	11	11	**10**	11	11	10	10	11	11
11	11	11	10	11	11	11	11	11	11	11	12	11	**11**	11	11	11	10	11	11
11	11	11	11	11	11	11	11	11	11	11	13	11	**11**	11	11	11	10	11	11
11	11	11	11	12	11	11	14	11	11	11	14	11	**11**	11	11	11	11	11	11
12	11	12	11	12	12	11	14	11	11	14	14	13	**11**	11	11	12	11	11	11
14	14	14	11	12	14	14	14	11	14	14	14	14	**14**	14	13	14	12	12	11

1	2	2	1	0	1	0	0	1	1	3	1	2	**3**	0	3	2	1	1	2
1	2	2	3	2	2	2	2	3	5	2	2	2	**5**	1	2	3	3	3	3
2	1	2	0	3	2	1	3	0	1	2	5	2	**1**	1	1	2	1	1	0

X	4	5	6	4	5	5	3	5	4	7	7	8	6	**9**	2	6	7	5	5	5
	16	15	14	16	15	15	17	15	16	13	13	12	14	**11**	18	14	13	15	14	15
	16	15	14	16	15	15	17	15	16	13	13	12	14	**11**	18	14	13	15	14	15
Y	20	20	20	20	20	20	20	20	20	20	20	20	20	**20**	20	20	20	20	19	20

25%

35 M1

20 M2

1	2	3	4	5
6	7	**8**	9	10
11	12	13	14	15

5	1	1	1	1	1	*1*	*1*	1	1	1	1	1	1	1	1	1	1	1	1
5	1	1	1	1	1	*1*	**4**	1	1	1	1	1	1	1	2	1	1	1	1
5	1	1	1	1	2	*1*	**4**	1	1	1	1	1	1	1	5	1	1	1	1
6	2	1	1	2	2	*1*	*5*	1	1	2	1	1	3	1	5	1	4	1	1
6	3	1	2	5	4	*1*	*5*	1	1	3	5	1	4	2	5	2	4	1	1
6	5	2	2	5	5	*1*	*5*	4	1	5	5	1	5	5	5	2	4	1	1
9	5	3	2	5	5	*1*	*5*	5	5	5	5	4	5	5	5	6	4	1	4
9	9	5	5	6	5	**2**	*5*	5	5	6	5	4	6	5	6	9	5	1	4
9	9	5	5	6	6	*5*	*5*	5	9	8	5	5	6	5	9	10	5	2	5
9	9	9	5	10	6	*5*	*6*	6	9	9	7	5	6	9	9	10	5	4	6
10	10	10	5	10	9	*5*	**7**	6	9	10	9	5	10	9	9	11	6	4	6
11	10	10	5	10	10	**9**	**8**	10	10	11	10	6	10	10	10	11	9	5	8
11	10	10	6	10	10	**9**	**9**	11	11	11	10	6	10	10	10	11	10	5	9
11	10	10	7	11	10	**9**	10	11	11	11	10	8	11	11	10	11	10	5	9
11	10	10	10	11	11	*10*	11	11	11	11	10	9	11	11	11	11	10	9	10
11	10	11	11	11	11	*11*	11	11	11	11	11	10	11	11	11	11	11	10	11
11	10	11	11	11	11	*11*	11	11	11	11	11	10	11	11	11	11	11	11	11
14	11	11	11	11	11	*11*	14	11	12	11	11	11	11	11	11	11	11	11	11
14	11	11	14	11	12	**12**	14	14	12	12	11	11	14	11	11	11	11	11	11

	14	12	11	14	11	14	**14**	15	14	12	13	14	11	15	15	11	12	14	12	11
	4	3	1	1	0	1	3	3	0	3	2	2	2	0	2	3	1	1	1	3
	0	2	2	3	1	3	1	2	1	0	2	0	2	2	1	1	2	4	3	2
	3	1	0	2	0	2	2	2	2	3	2	1	0	1	0	0	1	1	1	0
X	7	6	3	6	1	6	6	7	3	6	6	3	4	3	3	4	4	6	5	5
	13	14	17	14	19	14	14	13	17	14	14	17	16	17	17	16	16	14	15	15
	13	14	17	14	19	14	14	13	17	14	14	17	16	17	17	16	16	14	15	15
Y	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20

30%

	1	2	3	4	5
35 M1	6	7	**8**	9	10
20 M2	11	12	13	14	15

	1	1	1	1	1	1	1	1	1	2	1	1	1	1	1	1	1	1	1	1
	1	1	1	1	1	1	1	1	1	5	1	1	1	1	1	1	1	1	1	1
	1	1	1	1	1	1	1	1	1	5	1	1	1	1	1	2	1	1	1	1
	1	1	1	1	1	2	2	1	1	5	2	2	1	1	2	2	1	2	1	1
	1	1	1	1	2	5	2	4	2	5	4	2	2	1	2	2	1	2	1	2
	2	1	2	2	2	5	2	4	4	5	5	2	2	1	4	5	2	4	1	2
	5	4	4	4	4	5	2	5	5	8	5	5	3	2	5	5	2	5	1	5
	5	5	5	4	5	5	5	5	5	9	6	5	5	4	5	5	2	5	2	5
	5	5	5	5	5	5	8	5	5	9	9	7	5	5	5	5	4	5	2	5
	6	6	5	5	6	5	9	5	5	11	10	8	6	5	5	7	5	6	6	5
	6	9	5	5	6	6	9	5	5	11	11	9	7	5	6	8	5	9	9	9
	7	9	5	5	7	7	9	5	9	11	11	9	8	5	9	9	5	9	9	9
	7	11	9	5	9	9	11	8	9	11	11	9	9	6	9	10	6	10	9	10
	8	11	9	5	9	10	11	9	9	11	11	10	9	7	9	10	10	11	10	10
	9	11	9	8	11	10	11	9	11	11	11	11	9	9	11	10	11	11	11	10
	10	11	10	9	11	11	11	9	11	11	11	11	9	9	11	11	11	11	11	11
	11	11	11	11	11	11	11	11	11	11	11	11	11	9	11	11	11	11	11	11
	11	11	11	11	11	11	11	11	11	13	11	11	11	10	11	11	11	11	11	11
	13	12	11	11	12	11	11	11	11	14	12	12	11	11	11	11	11	12	11	12
	14	14	11	12	14	11	11	11	12	14	15	14	11	11	11	12	11	13	13	12
	4	2	3	2	3	2	4	4	3	3	1	5	6	4	3	3	0	2	3	2
	1	1	2	3	3	1	4	2	2	0	2	3	3	2	3	3	4	3	2	2
	2	2	0	1	2	0	0	0	1	3	1	2	0	0	0	1	0	2	1	2
X	7	5	5	6	8	3	8	6	6	6	4	10	9	6	6	7	4	7	6	6

	13	15	15	14	12	17	12	14	14	13	16	10	11	14	14	13	16	13	14	14
	13	15	15	14	12	17	12	14	14	13	16	10	11	14	14	13	16	13	14	14
Y	20	20	20	20	20	20	20	20	20	19	20	20	20	20	20	20	20	20	20	20

30%

	1	2	3	4	5
35 M1	6	7	**8**	9	10
20 M2	11	12	13	14	15

1	1	1	1	1	1	1	1	1	2	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	5	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	5	1	1	1	1	1	2	1	1	1	1
1	1	1	1	1	2	2	1	1	5	2	**2**	1	1	2	2	1	2	1	1
1	1	1	1	2	5	2	4	2	5	4	**2**	2	1	2	2	1	2	1	2
2	1	2	2	2	5	2	4	4	5	5	**2**	2	1	4	5	2	4	1	2
5	4	4	4	4	5	2	5	5	8	5	5	3	2	5	5	2	5	1	5
5	5	5	4	5	5	5	5	5	9	6	5	5	4	5	5	2	5	2	5
5	5	5	5	5	5	8	5	5	9	9	**7**	5	5	5	5	4	5	2	5
6	6	5	5	6	5	9	5	5	11	10	**8**	6	5	5	7	5	6	6	5
6	9	5	5	6	6	9	5	5	11	11	**9**	7	5	6	8	5	9	9	9
7	9	5	5	7	7	9	5	9	11	11	**9**	8	5	9	9	5	9	9	9
7	11	9	5	9	9	11	8	9	11	11	**9**	9	6	9	10	6	10	9	10
8	11	9	5	9	10	11	9	9	11	11	10	9	7	9	10	10	11	10	10
9	11	9	8	11	10	11	9	11	11	11	11	9	9	11	10	11	11	11	10
10	11	10	9	11	11	11	9	11	11	11	11	9	9	11	11	11	11	11	11
11	11	11	11	11	11	11	11	11	11	11	11	11	9	11	11	11	11	11	11
11	11	11	11	11	11	11	11	11	13	11	11	11	10	11	11	11	11	11	11
13	12	11	11	12	11	11	11	11	14	12	**12**	11	11	11	11	11	12	11	12
14	14	11	12	14	11	11	11	12	14	15	**14**	11	11	11	12	11	13	13	12

	4	2	3	2	3	2	4	4	3	3	1	5	6	4	3	3	0	2	3	2
	1	1	2	3	3	1	4	2	2	0	2	3	3	2	3	3	4	3	2	2
	2	2	0	1	2	0	0	0	1	3	1	2	0	0	0	1	0	2	1	2
X	7	5	5	6	8	3	8	6	6	6	4	10	9	6	6	7	4	7	6	6
	13	15	15	14	12	17	12	14	14	13	16	10	11	14	14	13	16	13	14	14
	13	15	15	14	12	17	12	14	14	13	16	10	11	14	14	13	16	13	14	14
Y	20	20	20	20	20	20	20	20	20	19	20	20	20	20	20	20	20	20	20	20

35%

35 M1
20 M2

1	2	3	4	5
6	7	**8**	9	10
11	12	13	14	15

	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2
	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2
	1	1	1	1	1	1	1	2	1	1	1	1	1	1	1	2	1	1	1	2
	1	2	1	1	1	1	1	2	2	1	2	1	1	2	3	5	1	1	2	2
	2	2	1	1	2	1	1	2	2	5	2	1	5	2	3	5	5	1	5	5
	2	5	2	2	2	2	1	2	2	5	5	1	5	2	5	5	5	2	5	5
	2	5	2	2	5	2	1	2	5	5	6	5	5	5	5	5	5	2	8	5
	5	5	2	5	5	4	2	5	5	7	8	5	5	5	5	5	5	4	8	5
	5	5	5	5	5	5	2	5	5	8	9	5	5	5	5	5	5	5	9	8
	5	6	5	5	8	5	2	5	5	9	9	5	5	5	5	5	5	6	9	9
	5	9	5	7	8	5	2	5	5	9	9	5	8	5	6	8	5	6	9	9
	5	9	7	9	9	5	2	5	7	9	9	8	9	5	7	8	6	8	11	10
	5	9	9	9	9	5	5	7	7	9	10	9	9	5	7	9	9	9	11	11
	5	10	10	9	9	9	5	7	8	9	11	9	9	8	8	9	9	11	11	11
	8	11	11	10	9	11	8	7	8	9	11	9	9	8	8	10	9	11	11	11
	8	11	11	11	10	11	11	9	8	9	11	10	11	8	9	11	11	11	11	11
	9	11	11	11	11	11	11	11	8	9	11	11	11	8	11	11	11	11	11	11
	11	11	11	11	11	11	11	11	9	11	11	11	11	9	11	11	11	11	11	11
	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11
	11	11	11	12	11	11	11	14	11	11	15	11	11	11	13	11	11	15	11	11
	3	3	2	4	6	1	1	4	7	10	5	4	5	5	5	4	3	2	5	3
	3	2	3	2	2	3	5	5	3	0	2	0	0	3	2	1	0	3	1	3
	0	0	0	1	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0
X	6	5	5	7	8	4	6	10	10	10	7	4	5	8	8	5	3	5	6	6
	14	15	15	13	12	16	14	10	10	10	13	16	15	12	12	15	17	15	14	13
	14	15	15	13	12	16	14	10	10	10	13	16	15	12	12	15	17	15	14	13
Y	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	19

40%

35 M1
20 M2

1	2	3	4	5
6	7	**8**	9	10
11	12	13	14	15

1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1

1	1	1	1	1	1	2	1	1	1	1	1	1	1	1	1	2	1	1	1
1	1	2	1	1	1	5	1	1	1	1	4	1	1	1	1	2	1	1	1
1	1	2	1	1	1	5	1	4	1	1	4	1	1	1	5	5	1	1	1
1	1	3	1	1	1	5	1	5	1	5	5	1	1	2	5	5	1	1	1
4	1	5	2	1	1	5	1	5	1	5	7	1	2	2	5	5	1	1	1
5	2	5	5	2	2	7	2	7	1	5	8	2	4	5	5	5	2	5	1
5	5	5	5	4	5	7	2	8	2	5	9	2	5	5	5	5	4	5	2
5	5	5	5	5	5	7	5	8	5	5	9	5	5	5	5	5	5	5	3
5	7	5	5	5	5	8	5	9	5	5	9	5	5	5	5	5	5	5	4
5	8	5	6	5	5	8	5	9	5	7	10	5	5	7	6	9	6	7	5
5	8	8	6	5	5	8	8	9	5	8	10	5	5	8	7	9	7	7	5
8	8	8	7	6	5	9	9	11	5	9	11	5	7	9	7	9	7	9	5
8	9	9	8	7	5	9	10	11	9	9	11	7	7	9	8	9	7	9	5
11	9	9	9	7	5	9	11	11	9	9	11	8	7	9	9	11	8	11	5
11	11	9	9	8	7	9	11	11	10	9	11	8	8	9	9	11	9	11	7
11	11	11	9	8	7	9	11	11	11	9	11	8	11	9	9	11	9	11	8
11	11	11	11	9	9	11	11	11	11	11	11	9	11	10	11	11	11	11	9
11	11	11	11	11	9	11	11	11	11	11	11	9	11	11	11	11	11	11	9
11	12	11	11	11	11	11	11	11	12	11	13	11	12	11	11	11	11	12	11

	2	6	5	5	5	4	11	2	6	2	7	5	6	4	7	6	4	6	4	4
	1	1	3	1	2	1	1	2	1	1	0	2	2	2	2	0	2	2	0	3
	0	1	0	0	0	0	0	0	0	1	0	1	0	1	0	0	0	0	1	0
X	3	8	8	6	7	5	12	4	7	4	7	8	8	7	9	6	6	8	5	7
	17	12	12	14	13	15	8	16	13	16	13	12	12	13	11	14	14	12	15	13
	17	12	12	14	13	15	8	16	13	16	13	12	12	13	11	14	14	12	15	13
Y	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20

45%

	1	2	3	4	5
35 M1	6	7	**8**	9	10
20 M2	11	12	13	14	15

1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	2	1	1	1	1	1	1	2	1	1	1	1	2	1
1	2	1	1	1	1	2	2	1	1	1	1	1	5	1	1	1	5	3	1
1	2	1	2	1	1	2	2	1	1	1	2	1	5	2	1	1	5	4	2
2	5	2	5	1	1	2	2	1	1	1	2	2	5	5	1	2	5	5	2
4	5	2	5	2	2	3	4	2	2	1	5	2	7	5	4	2	5	5	2
5	7	3	5	5	2	4	5	5	5	1	5	2	8	5	4	4	5	5	5
5	7	4	5	5	5	5	5	5	5	2	5	4	8	7	4	4	7	5	5

	5	7	5	5	5	5	5	5	5	5	2	5	5	8	7	5	5	7	5	5
	7	8	5	5	5	5	5	5	5	5	5	5	5	9	8	5	5	7	5	5
	7	8	5	5	5	5	5	7	7	7	5	5	5	9	8	5	5	7	7	5
	8	8	5	7	7	5	5	7	7	8	5	5	5	9	9	6	5	9	8	5
	8	9	6	7	8	8	6	9	8	9	5	7	5	9	9	7	5	9	9	7
	8	9	7	7	9	8	8	11	9	9	7	7	5	11	9	7	5	11	9	7
	9	9	7	9	10	8	8	11	9	9	7	7	8	11	9	8	5	11	9	8
	11	10	7	9	11	8	9	11	9	9	7	7	8	11	9	8	7	11	9	8
	11	11	8	9	11	9	9	11	10	11	7	9	11	11	11	8	9	11	11	8
	11	11	9	11	11	10	9	11	10	11	8	11	11	11	11	9	11	11	11	11
	11	12	11	11	11	11	11	11	11	13	9	11	11	11	11	9	11	11	11	11
	11	13	11	11	11	11	12	13	11	13	12	11	11	13	13	12	11	11	11	11
	6	9	5	6	3	5	5	3	6	6	6	5	2	8	9	7	2	6	6	5
	2	2	4	1	1	2	6	4	1	1	2	2	4	1	1	3	4	0	3	3
	0	2	0	0	0	0	1	1	0	2	1	0	0	1	1	1	0	0	0	0
X	8	13	9	7	4	7	12	8	7	9	9	7	6	10	11	11	6	6	9	8
	12	7	11	13	16	13	8	12	13	11	11	13	14	10	9	9	14	14	11	12
	12	7	11	13	16	13	8	12	13	11	11	13	14	10	9	9	14	14	11	12
Y	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20

50%

35 M1

20 M2

1	2	3	4	5
6	7	**8**	9	10
11	12	13	14	15

1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	2	1	1	1	1	1	1	2	2	1	1	1	1	2	1	1
1	2	1	1	5	1	1	1	2	1	1	2	2	2	1	1	1	2	1	1
2	2	2	1	5	1	2	1	2	1	2	2	2	2	1	2	2	2	2	1
5	2	2	1	5	4	2	4	5	1	4	5	5	4	1	2	2	5	2	2
5	4	2	1	5	5	5	5	5	4	4	5	5	5	2	5	5	5	2	4
5	4	2	1	5	5	5	5	5	4	5	5	5	5	5	5	5	5	2	5
5	4	4	1	5	5	5	5	5	5	5	7	5	5	5	6	5	5	5	5
5	4	5	2	5	5	5	5	5	5	5	7	5	5	5	7	7	5	5	5
5	5	5	5	7	5	5	7	5	5	7	7	5	5	5	7	7	6	7	5
7	5	5	5	7	5	5	7	7	5	7	7	7	5	7	8	7	7	7	5
7	5	5	7	7	7	7	7	7	5	7	7	7	5	7	9	7	7	7	5
7	5	7	7	7	7	8	7	8	5	7	7	7	7	7	9	7	7	7	5
7	7	7	7	8	7	8	9	9	7	7	7	7	7	7	9	7	7	7	9

	7	7	8	7	8	7	9	11	9	7	8	7	7	7	8	11	11	9	7	9
	8	7	9	9	9	9	9	11	9	8	11	8	9	7	11	11	11	9	8	9
	9	9	11	11	11	11	11	11	9	9	11	11	9	9	11	11	11	9	8	11
	11	11	11	12	11	11	11	11	11	9	11	11	11	11	11	11	11	11	11	11
	13	11	12	13	11	11	11	11	11	9	15	11	11	11	12	11	11	11	11	11
	7	4	4	5	7	5	5	5	7	6	6	9	7	5	5	6	6	7	8	3
	1	7	5	1	1	1	2	1	2	2	3	3	3	3	1	2	2	3	4	2
	1	0	1	2	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
X	9	11	10	8	8	6	7	6	9	8	9	12	10	8	7	8	8	10	12	5
	11	9	10	12	12	14	13	14	11	12	11	8	10	12	13	12	12	10	8	15
	11	9	10	12	12	14	13	14	11	12	11	8	10	12	13	12	12	10	8	15
Y	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20

55%

35 M1

20 M2

1	2	3	4	5
6	7	**8**	9	10
11	12	13	14	15

1	1	*1*	1	1	*1*	1	1	1	1	1	1	1	1	1	1	1	1	1	1
1	1	*1*	1	1	*1*	1	1	1	1	1	1	1	1	1	1	1	1	1	1
1	1	*1*	1	1	*1*	1	2	1	1	1	2	1	1	1	1	1	2	1	2
1	1	**2**	1	1	*5*	2	2	1	1	1	2	1	2	1	1	2	2	1	2
1	1	**2**	1	2	*5*	2	2	1	4	1	2	2	2	1	1	2	2	1	5
2	2	*5*	1	5	*5*	2	2	2	5	1	5	2	2	1	2	2	2	1	5
2	5	**7**	2	5	*5*	5	5	2	5	1	5	5	4	2	2	5	5	1	5
5	5	**7**	2	5	**7**	5	5	2	5	2	5	5	5	2	2	5	5	2	7
5	5	**7**	5	5	**7**	5	5	2	5	2	7	5	5	2	2	5	5	2	7
5	6	**7**	5	5	**7**	5	5	5	7	5	7	5	5	5	5	5	5	2	7
5	7	**7**	5	5	**7**	7	5	5	7	7	7	7	5	5	5	7	5	5	7
7	7	**7**	5	7	**7**	7	5	5	7	7	9	7	7	5	5	7	7	5	7
7	7	**9**	5	7	**7**	7	5	5	7	7	9	7	7	5	7	7	7	5	7
7	7	**9**	7	7	**9**	7	5	7	7	9	9	8	7	7	7	7	7	7	7
7	9	**9**	7	7	**9**	7	7	7	7	9	9	9	9	7	7	7	9	7	9
7	9	**9**	7	9	**9**	7	7	7	7	9	9	9	9	9	7	7	9	9	9
7	9	**9**	9	9	**9**	7	7	7	11	9	9	9	11	9	9	9	9	9	9
9	11	*11*	9	11	**9**	9	7	9	11	11	11	9	11	9	9	9	9	11	9
11	11	*11*	11	11	*11*	11	11	11	11	13	11	9	11	9	9	11	11	11	9
11	11	**13**	11	11	***13***	11	11	11	15	13	11	13	11	11	11	15	11	11	11

	7	7	11	5	6	11	8	4	5	7	7	9	9	5	6	7	8	7	4	12
	2	1	2	2	1	0	3	4	4	1	2	3	2	4	3	4	3	4	3	2
	0	0	1	0	0	1	0	0	0	0	2	0	1	0	0	0	0	0	0	0
X	9	8	14	7	7	12	11	8	9	8	11	12	12	9	9	11	11	11	7	14
	11	12	6	13	13	8	9	12	11	12	9	8	8	11	11	9	9	9	13	6
	11	12	6	13	13	8	9	12	11	12	9	8	8	11	11	9	9	9	13	6
Y	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20

60%

	1	2	3	4	5
35 M1	6	7	**8**	9	10
20 M2	11	12	13	14	15

1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	1
2	1	1	2	1	2	1	1	1	2	1	1	1	1	1	1	1	1	2	1
2	2	2	2	1	2	1	1	2	2	2	1	2	2	1	1	1	1	2	2
5	2	2	2	2	5	1	1	2	2	2	1	2	2	1	1	1	1	2	2
5	5	2	2	2	5	1	1	5	5	5	1	5	2	1	1	1	2	5	2
5	5	5	5	5	5	1	2	5	5	5	1	5	2	2	1	1	2	5	5
7	7	5	5	5	5	2	2	7	5	5	2	5	5	2	2	2	2	5	5
7	7	5	5	5	5	2	7	7	5	5	2	7	5	5	2	5	2	5	6
7	7	7	5	7	5	2	7	7	5	5	5	7	5	5	2	5	5	5	7
7	7	9	5	7	5	2	7	7	7	7	5	7	5	7	5	7	5	5	7
7	9	9	5	7	7	2	7	9	7	7	5	7	7	7	5	7	5	7	9
7	9	9	5	7	7	5	7	9	7	9	5	7	7	7	7	7	5	7	9
9	9	11	5	9	9	5	7	9	9	9	7	7	7	7	7	7	7	7	9
9	9	11	5	9	9	5	7	11	9	9	7	9	7	9	7	7	7	9	9
9	11	11	7	9	11	7	9	11	9	11	7	11	9	11	7	7	7	9	9
9	11	11	7	10	11	7	9	11	9	11	7	11	9	11	7	9	9	9	11
11	11	11	7	11	11	9	11	11	9	11	11	11	9	11	9	9	9	9	11
11	14	11	9	12	11	9	13	11	9	11	11	11	11	11	9	11	9	11	11
12	14	12	9	14	14	11	14	14	11	14	14	11	13	15	9	14	10	11	12

	10	8	4	5	7	4	4	9	7	9	5	4	7	7	5	8	8	6	7	7
	2	2	3	4	2	2	5	2	2	3	2	2	2	4	2	3	1	4	4	3
	1	2	1	0	2	1	0	2	1	0	1	1	0	1	0	0	1	0	0	1
X	13	12	8	9	11	7	9	13	10	12	8	7	9	12	7	11	10	10	11	11
	7	8	12	11	9	13	11	7	10	8	12	13	11	8	13	9	10	10	9	9

	7	8	12	11	9	13	11	7	10	8	12	**13**	11	8	13	9	10	10	9	9
Y	20	20	20	20	20	20	20	20	20	20	20	**20**	20	20	20	20	20	20	20	20

65%

	1	2	3	4	5
35 M1	6	7	**8**	9	10
20 M2	11	12	13	14	15

1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	2	1	1	1	1	1	1	2	2	1	1	1	1	1
1	2	1	1	1	1	2	1	1	1	1	1	1	2	2	1	1	1	1	2
1	2	1	1	1	1	2	2	2	1	1	1	2	2	5	1	1	1	1	2
1	2	1	2	1	2	2	5	2	2	1	2	2	2	5	1	1	1	2	2
1	2	1	5	1	2	5	5	2	5	2	2	5	5	5	2	2	2	5	2
2	2	2	5	2	5	5	5	2	5	5	2	5	7	5	2	2	2	5	2
5	5	2	5	2	5	7	5	5	5	5	5	5	7	5	2	2	5	5	5
7	5	5	5	2	6	7	5	5	5	5	5	5	7	5	2	5	5	7	5
7	5	5	5	2	7	7	7	5	5	5	7	7	7	7	5	5	7	7	7
7	7	7	5	2	7	7	7	7	7	7	7	7	7	7	5	5	7	7	7
7	9	9	7	2	7	7	7	7	7	7	7	7	7	7	7	5	7	7	7
7	9	9	9	5	7	7	7	7	7	7	7	7	9	7	7	7	7	7	7
7	9	9	9	5	11	7	7	7	9	7	7	7	9	9	7	7	7	9	9
9	9	11	9	7	11	9	7	11	11	9	9	7	9	9	9	9	9	9	11
9	9	11	11	9	11	9	9	11	11	9	9	9	9	11	9	9	11	9	11
9	11	11	11	9	11	9	9	11	11	9	10	9	9	11	11	9	11	9	11
11	11	11	11	11	11	9	9	11	11	9	11	9	11	11	11	11	11	11	11
11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	15	11	15
15	15	11	15	15	15	11	15	12	12	11	15	11	11	11	12	15	15	11	15

9	6	4	4	3	4	11	9	4	4	8	7	9	11	6	5	5	6	9	5
1	5	2	1	6	2	4	1	4	1	1	3	2	4	2	4	3	2	1	5
0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	1	0	0	0	0

X	10	11	6	5	9	6	15	10	9	6	9	**10**	11	15	8	10	8	8	10	10
	10	9	14	15	11	14	5	10	11	14	11	**10**	9	5	12	10	12	12	10	10
	10	9	14	15	11	14	5	10	11	14	11	**10**	9	5	12	10	12	12	10	10
Y	20	20	20	20	20	20	20	20	20	20	20	**20**	20	20	20	20	20	20	20	20

70%

	1	2	3	4	5
35 M1	6	7	**8**	9	10

20 M2

11	12	13	14	15

1	1	1	1	1	1	1	1	1	1	1	2	1	1	1	1	1	1	1	1
2	2	1	1	1	1	1	2	1	1	1	2	1	1	1	1	1	1	2	1
2	2	1	2	1	1	1	5	2	1	2	2	1	1	1	2	1	2	2	1
5	2	5	2	1	1	2	5	2	2	2	2	1	1	1	2	1	2	5	1
5	2	5	5	1	1	2	6	5	2	2	2	1	2	1	2	1	2	5	2
5	2	5	5	2	2	2	7	5	5	2	5	2	2	2	2	2	2	5	2
7	5	5	6	2	2	5	7	7	5	5	5	7	2	2	2	2	2	5	2
7	5	7	7	5	2	5	7	7	7	5	5	7	5	2	7	2	5	7	5
7	7	7	7	7	2	5	7	7	7	7	7	7	5	5	7	7	5	7	5
9	7	7	7	7	2	7	7	7	9	7	7	9	5	5	9	7	5	7	5
9	9	7	9	7	5	7	7	7	9	7	7	9	7	7	9	7	7	7	9
9	9	7	9	9	5	9	7	7	9	9	9	9	7	9	9	7	7	9	9
11	9	9	9	9	7	9	9	7	9	11	9	9	7	9	10	9	9	9	9
11	9	9	9	9	7	9	9	11	9	11	9	9	9	9	11	9	10	9	11
11	11	9	9	9	7	9	11	11	9	11	9	11	9	11	11	9	11	9	11
11	11	9	11	11	9	11	11	11	11	11	11	11	9	11	11	9	11	9	11
11	11	9	11	11	9	11	11	11	11	11	11	11	11	11	11	9	11	11	11
11	11	11	11	15	11	11	11	11	11	11	11	11	11	15	11	11	11	11	11
11	15	11	11	15	11	11	11	11	11	11	11	11	15	15	11	11	15	11	15
15	15	15	15	15	15	15	11	15	15	15	15	11	15	15	15	15	15	11	15

6	6	10	8	7	5	6	9	7	8	4	7	8	6	4	5	9	3	9	3
2	5	0	2	2	5	3	1	2	2	4	4	1	3	3	5	3	5	2	3
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

X	8	11	10	10	9	10	9	10	9	10	8	**11**	9	9	7	10	12	8	11	6
	12	9	10	10	11	10	11	10	11	10	12	8	11	11	13	10	8	12	9	14
	12	9	10	10	11	10	11	10	11	10	12	**8**	11	11	13	10	8	12	9	14
Y	20	20	20	20	20	20	20	20	20	20	20	**19**	20	20	20	20	20	20	20	20

75%

	1	2	3	4	5	
35 M1	6	7	**8**	9	10	M1
20 M2	11	12	13	14	15	M2

1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
2	1	1	1	1	2	2	1	1	1	2	2	2	2	1	2	1	2	1	1
2	1	1	1	1	2	2	1	1	2	2	2	2	2	1	2	1	2	2	1
2	1	2	1	2	2	2	2	2	2	2	2	2	2	1	5	2	2	2	1
2	1	2	2	2	5	2	2	2	5	2	2	2	2	2	5	2	2	2	2
2	2	5	2	2	7	2	2	2	5	5	2	5	2	2	5	2	4	2	2

5	2	5	2	2	7	2	5	2	5	9	5	5	2	2	5	5	5	2	2
5	2	7	2	5	7	5	5	5	7	9	5	6	2	2	5	7	5	2	2
5	2	7	6	5	9	5	7	5	7	9	5	7	2	5	5	7	5	2	2
5	2	9	7	5	9	6	7	5	7	9	7	7	2	5	5	7	5	2	5
7	2	9	7	7	9	7	7	7	7	9	7	9	5	5	5	7	5	5	5
7	5	9	7	7	9	7	7	7	9	9	8	9	7	5	7	9	7	5	5
7	6	11	7	7	9	7	9	9	9	11	9	9	7	5	7	9	7	5	5
9	7	11	7	9	9	7	9	9	9	11	9	11	7	7	7	9	7	9	7
9	7	11	9	11	9	9	9	9	9	11	9	11	9	7	7	11	7	9	9
9	9	11	9	11	11	9	9	11	11	11	9	11	9	9	9	11	9	11	9
9	9	12	9	11	11	9	11	11	11	11	11	11	11	9	11	11	9	11	9
11	11	15	11	15	11	11	11	11	11	11	11	11	11	9	11	11	9	11	11
11	11	15	11	15	11	11	11	15	12	15	15	11	15	11	11	11	11	11	11
11	11	15	15	15	11	15	15	15	15	15	15	11	15	11	15	11	15	11	15

7	4	5	8	4	10	7	8	5	8	6	7	5	5	5	5	7	7	2	4
5	6	2	4	4	3	6	3	4	2	4	5	4	9	4	2	3	5	8	5
0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0

X	12	10	8	12	8	13	13	11	9	11	10	12	9	14	9	7	10	12	10	9
	8	10	12	8	12	7	7	9	11	9	10	8	11	6	11	13	10	8	10	11
	8	10	12	8	12	7	7	9	11	9	10	8	11	6	11	13	10	8	10	11
Y	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20

80%	1	2	3	4	5	
35 M1	6	7	**8**	9	10	M1
20 M2	11	12	13	14	15	M2

1	1	1	1	2	1	1	1	1	1	1	1	1	1	1	1	2	2	1	1
1	1	1	1	2	2	2	2	2	1	1	1	2	1	2	1	2	2	1	1
1	2	1	1	5	2	2	2	2	1	1	2	2	2	5	1	2	2	2	2
5	2	3	2	5	2	2	2	2	2	2	2	2	4	5	2	7	2	2	2
5	2	5	2	5	5	2	2	2	2	2	2	2	5	5	2	7	5	2	2
7	2	5	2	7	5	2	2	2	2	5	2	2	5	5	2	7	5	4	7
7	2	7	2	7	5	2	5	5	2	5	2	2	5	7	2	7	7	5	7
7	2	7	2	7	7	5	5	5	2	5	2	5	7	7	2	9	7	5	7
7	4	7	2	7	7	5	5	5	7	7	5	5	7	7	5	9	7	5	7
7	5	7	7	7	7	5	7	5	7	7	7	5	7	7	7	9	7	7	7
7	5	7	7	8	7	5	7	7	7	7	7	5	7	7	7	9	7	7	7
7	7	8	8	9	7	5	7	7	7	7	7	7	7	7	7	9	7	7	8
7	7	9	8	9	7	5	7	7	7	7	7	7	8	8	7	9	9	7	9
9	7	9	9	9	7	7	7	7	7	9	9	7	8	9	7	9	9	7	9

9	9	9	9	11	7	7	8	7	9	9	9	7	9	9	9	9	9	7	9
11	9	10	9	11	8	7	9	9	9	9	9	9	9	9	9	11	9	9	9
11	9	11	11	14	9	9	9	9	10	9	9	11	11	11	14	11	11	9	9
13	10	11	11	15	9	9	9	10	11	11	11	14	11	11	14	11	11	10	9
15	11	14	14	15	14	11	9	14	15	15	11	15	14	11	15	11	14	11	14
15	15	15	15	15	15	15	15	15	15	15	15	15	14	14	15	11	15	14	15

10	6	9	7	9	11	5	10	7	8	9	8	5	9	10	7	12	10	8	13
0	7	1	6	1	3	6	5	5	5	2	6	6	2	1	5	2	3	4	3
1	0	1	1	1	1	0	0	1	0	0	0	1	2	1	2	0	1	1	1

X	11	13	11	14	11	15	11	15	13	13	11	14	12	13	12	14	14	14	13	17
	9	7	9	6	8	5	9	5	7	7	9	6	8	7	8	6	5	5	7	3
	9	7	9	6	8	5	9	5	7	7	9	6	8	7	8	6	5	5	7	3
Y	20	20	20	20	19	20	20	20	20	20	20	20	20	20	20	20	19	19	20	20

85%

35 M1

20 M2

1	2	3	4	5
6	7	**8**	9	10
11	12	13	14	15

M1

M2

1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	2	1	1	1	1	1	1	1	1	1	1	1	1	2
1	1	1	2	2	2	2	1	2	2	1	1	1	2	1	1	1	1	1	2
2	1	2	2	2	2	2	2	2	2	1	2	2	2	2	1	2	2	1	5
2	2	2	2	2	2	2	2	2	2	1	2	2	2	2	1	2	2	2	7
2	2	2	2	5	2	2	2	5	2	2	2	4	2	2	2	2	2	2	7
4	2	2	2	7	4	2	2	5	5	4	2	5	2	2	2	2	2	5	7
5	2	2	5	7	7	4	7	5	5	7	2	5	2	5	2	2	4	7	7
7	2	7	5	7	7	4	7	7	7	7	4	5	4	5	2	2	7	7	7
7	2	7	7	7	7	5	7	7	7	7	4	7	5	5	5	2	7	7	7
7	2	7	7	7	7	7	7	7	7	7	5	7	7	7	5	7	7	7	7
7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	5	7	7	7	9
7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	5	7	7	7	9
7	7	7	7	7	9	7	9	9	7	7	7	7	9	7	7	7	7	7	9
9	7	7	7	7	9	9	9	9	9	9	7	9	9	7	7	9	7	9	9
9	7	9	7	9	9	9	9	9	9	9	7	9	9	7	9	11	9	9	9
10	9	9	9	9	9	9	9	9	9	9	9	9	11	7	9	11	9	9	11
10	11	9	9	9	9	11	11	10	9	11	9	9	11	9	9	11	9	9	15
15	11	9	11	9	10	15	15	15	11	11	15	9	15	10	9	15	9	9	15
15	15	10	15	15	11	15	15	15	15	15	15	11	15	11	11	15	11	15	15

8	6	11	9	12	11	7	10	9	10	10	7	10	6	8	6	5	11	12	9

	0	3	0	0	0	0	1	0	0	0	0	2	0	1	0	1	2	0	0	0
	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
X	8	9	11	9	12	11	8	10	9	10	10	9	10	7	8	7	7	11	12	9
	5	3	1	4	1	2	4	3	4	3	3	3	3	5	5	5	5	1	1	4
	5	3	1	4	1	2	4	3	4	3	3	3	3	5	5	5	5	1	1	4
Y	13	12	12	13	13	13	12	13	13	13	13	12	13	12	13	12	12	12	13	13

90%

	1	2	3	4	5
35 M1	6	7	**8**	9	10
20 M2	11	12	13	14	15

M1

M2

1	2	1	1	1	1	1	2	1	1	1	1	1	1	1	1	1	1	1	1
1	2	1	1	2	2	1	2	1	1	1	1	1	2	1	2	1	1	1	2
2	2	1	2	2	2	1	2	1	1	2	2	1	2	2	2	1	1	1	2
2	2	1	4	2	2	2	4	2	2	2	2	1	2	2	2	2	1	2	2
2	2	2	5	2	5	4	4	2	2	2	2	1	2	5	2	2	2	2	2
2	2	2	7	2	5	4	5	2	2	2	5	1	2	5	5	2	2	4	2
2	4	2	7	4	5	5	7	5	2	2	7	2	2	7	7	2	2	4	5
4	5	2	7	5	7	7	7	7	2	2	7	2	5	7	7	7	2	7	7
7	7	7	7	7	7	7	7	7	4	7	7	7	7	7	7	7	7	7	7
7	7	7	7	7	7	7	7	7	4	7	7	7	7	7	7	7	7	7	9
7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	9
7	7	7	7	7	9	7	7	7	7	7	7	7	7	7	7	7	7	7	10
7	7	7	7	7	9	7	7	7	9	7	7	7	7	7	7	7	7	9	10
7	9	7	7	7	9	9	9	7	9	7	9	7	7	7	7	9	7	9	15
9	9	7	7	7	10	9	9	7	9	7	9	7	9	7	7	9	9	15	15
15	9	9	7	7	10	9	9	9	9	7	15	9	9	9	7	9	10	15	15
15	9	9	7	15	15	9	9	10	10	15	15	9	9	9	9	9	15	15	15
15	15	15	7	15	15	15	10	15	15	15	15	9	9	10	15	9	15	15	15
15	15	15	9	15	15	15	15	15	15	15	15	10	15	15	15	15	15	15	15
15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15

	7	9	9	12	8	7	10	10	9	6	8	8	10	10	10	10	11	7	7	4
	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
X	7	9	9	12	8	7	10	10	9	8	8	8	10	10	10	10	11	7	7	4
	5	4	3	1	5	6	3	3	4	4	4	5	2	3	3	3	2	5	6	9
	5	4	3	1	5	6	3	3	4	4	4	5	2	3	3	3	2	5	6	9

A.2.1.4 CS1 Additional ProMps Results

User 1019 Cell 10 Predictions

10%

	1	2	3	4	5
35 M1	6	7	**8**	9	10
20 M2	11	12	13	14	15

	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
	1	1	1	1	1	1	1	1	1	1	1	2	1	1	1	1	1	5	1	1
	1	5	1	1	1	2	1	1	1	1	1	5	1	1	1	1	1	5	1	1
	5	5	4	1	1	5	1	1	1	1	2	5	4	2	5	5	1	5	1	2
	5	5	5	2	1	5	1	5	2	1	4	5	5	4	5	5	1	5	1	5
	5	5	5	4	1	5	2	5	4	5	5	5	5	5	6	6	2	6	1	5
	8	5	5	4	2	8	4	5	5	5	5	6	5	5	6	8	2	9	1	10
	11	5	5	5	5	8	5	5	5	6	9	8	5	8	8	11	5	10	2	10
	11	5	5	5	5	10	9	6	5	8	11	10	6	8	10	11	5	10	5	10
	11	6	6	5	5	10	9	10	9	10	11	11	8	8	11	11	6	11	10	11
	11	10	10	7	10	10	11	11	11	11	11	11	10	10	11	11	10	11	10	11
	11	11	10	8	11	11	11	11	11	11	11	11	10	10	11	11	11	11	11	11
	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11
	11	11	11	11	11	11	11	11	11	11	14	11	11	11	11	11	11	11	11	11
	11	11	11	11	11	11	11	11	11	11	14	11	11	11	11	11	12	11	11	11
	11	11	13	11	11	11	11	12	11	11	14	11	11	11	11	11	14	11	11	14
	11	11	14	11	11	12	11	14	14	13	14	14	11	11	14	12	14	11	11	14
	14	11	14	11	14	13	14	14	14	14	14	14	11	14	14	13	14	11	14	14
	14	14	14	14	14	14	14	15	14	14	14	14	14	14	15	14	14	14	14	14
Same Row	1	1	2	1	1	5	2	1	1	2	1	2	3	5	2	1	1	3	2	3
Top Row	3	7	6	5	3	3	2	4	4	2	3	4	5	3	2	2	2	4	1	2
Bottom Row	2	1	4	1	2	2	2	3	3	3	6	3	1	2	3	2	4	1	2	4
X	6	9	12	7	6	10	6	8	8	7	10	9	9	10	7	5	7	8	5	9
	14	11	8	13	14	10	14	12	12	13	10	11	11	10	13	15	13	12	15	11
	14	11	8	13	14	10	14	12	12	13	10	11	11	10	13	15	13	12	15	11
Y	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20

15%

	1	2	3	4	5
35 M1	6	7	8	9	**10**
20 M2	11	12	13	14	15

	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
	1	1	1	1	1	1	1	1	1	1	1	1	5	1	1	1	5	1	1	1
	5	1	1	1	1	1	1	1	1	2	1	1	5	1	2	4	5	1	1	2
	5	5	5	1	1	1	1	1	2	2	4	5	5	1	5	5	5	1	5	5
	5	5	5	2	1	1	1	1	5	4	5	5	5	1	6	6	5	1	5	5
	8	5	6	5	1	5	1	4	5	5	5	5	5	1	8	6	5	2	6	6
	9	6	6	5	5	5	5	4	6	5	5	5	5	4	8	8	6	5	6	6
	10	7	8	5	5	5	5	5	6	5	5	5	6	5	9	9	9	5	8	9
	11	9	9	9	5	6	5	6	6	5	5	5	9	5	9	10	9	5	8	11
	11	11	10	11	5	8	8	8	6	5	6	8	9	6	10	11	9	6	9	11
	11	11	10	11	5	11	10	11	9	6	6	9	10	6	11	11	10	8	9	11
	11	11	10	11	6	11	10	11	10	6	8	9	11	6	11	11	11	9	10	11
	11	11	11	11	6	11	11	11	11	8	8	11	11	7	11	11	11	10	11	11
	11	11	11	11	9	12	11	11	11	9	11	11	11	7	11	11	11	11	11	11
	11	11	11	11	11	12	11	11	11	11	11	11	11	10	11	11	11	11	11	12
	11	11	11	11	11	12	11	12	11	11	12	11	11	11	11	11	11	11	12	13
	11	11	11	11	11	14	11	13	11	11	14	11	12	11	12	11	11	12	14	14
	14	12	12	11	12	14	12	14	11	11	14	11	12	11	12	12	11	14	14	14
	14	14	12	12	12	14	13	14	14	12	14	12	12	11	14	14	12	14	14	14
	15	14	14	13	14	14	14	14	14	14	15	15	14	15	14	14	14	14	14	14
Same Row	3	1	5	1	1	1	3	1	2	2	2	3	3	1	5	3	4	3	5	1
Top Row	3	3	2	3	5	3	3	3	2	6	6	6	6	3	1	2	5	3	2	2
Bottom Row	3	2	1	1	1	4	2	4	2	1	4	1	1	1	2	2	1	3	4	5
X	9	6	8	5	7	8	8	8	6	9	12	10	10	5	8	7	10	9	11	8
	11	14	12	15	13	12	12	12	14	11	8	10	10	15	12	13	10	11	9	12
	11	14	12	15	13	12	12	12	14	11	8	10	10	15	12	13	10	11	9	12
Y	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20

20%

	1	2	3	4	5
35 M1	6	7	8	9	**10**
20 M2	11	12	13	14	15

	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	5
	1	1	1	5	1	1	1	1	1	1	1	1	1	1	2	2	1	1	1	5
	5	1	2	5	2	2	1	1	1	2	5	1	2	1	5	5	1	5	1	5
	5	1	5	5	5	5	1	1	1	5	5	1	5	5	5	6	2	5	1	5
	5	1	5	6	5	5	2	2	5	5	5	1	5	5	5	7	6	5	1	8
	5	1	5	8	6	5	5	5	5	5	6	5	6	5	5	8	6	6	5	8
	5	1	5	8	6	5	5	6	6	5	6	5	7	6	6	11	8	6	5	8
	5	1	5	9	6	6	5	8	8	6	8	5	8	6	6	11	8	8	5	9
	9	5	9	10	8	6	5	10	11	6	9	6	9	6	8	11	8	11	9	9
	11	5	9	11	8	7	7	11	11	9	10	9	10	8	8	11	9	11	10	9
	11	5	9	11	10	9	8	11	11	9	10	9	11	8	9	11	11	11	11	10
	11	6	10	11	10	9	9	11	11	10	11	9	11	9	9	11	11	11	11	10
	11	6	10	11	11	10	11	11	11	11	11	11	11	9	9	11	11	11	11	11
	11	6	10	11	11	11	11	11	11	11	11	11	11	11	9	11	11	11	11	11
	11	9	11	11	11	11	11	11	11	11	11	11	11	11	10	11	11	11	14	11
	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	14	14	11
	14	11	11	14	11	11	11	14	11	14	11	11	11	11	11	11	11	14	14	11
	14	14	14	14	11	13	14	14	11	14	11	14	14	13	11	14	11	14	14	14
	14	14	14	14	14	14	14	14	11	14	14	15	14	15	11	14	14	14	14	14
Same Row	1	1	6	4	4	3	2	2	1	3	4	3	3	4	7	1	4	1	2	8
Top Row	6	3	5	3	2	4	4	1	2	4	3	3	2	3	4	1	0	3	3	4
Bottom Row	3	2	2	3	1	2	2	3	0	3	1	2	2	2	0	2	1	4	5	2
X	10	6	13	10	7	9	8	6	3	10	8	8	7	9	11	4	5	8	10	14
	10	14	7	10	13	11	12	14	17	10	12	12	13	11	9	16	15	12	10	6
	10	14	7	10	13	11	12	14	17	10	12	12	13	11	9	16	15	12	10	6
Y	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20

25%

	1	2	3	4	5
35 M1	6	7	8	9	**10**
20 M2	11	12	13	14	15

	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
	1	1	1	1	1	1	1	1	1	1	1	1	1	5	1	1	1	1	1	1
	1	1	1	1	1	1	1	5	5	1	1	5	1	5	5	1	1	3	2	1
	1	1	1	1	1	1	1	5	5	5	1	6	1	5	6	5	2	5	4	1
	1	4	1	1	1	5	5	5	6	5	1	6	1	5	8	5	2	5	4	4
	1	5	2	1	5	6	6	5	6	5	1	8	1	6	8	6	5	8	5	5
	1	5	6	5	8	6	6	5	6	6	1	8	1	7	9	9	5	8	6	5
	1	5	6	5	8	8	8	6	6	8	5	9	1	9	9	9	5	9	8	6
	5	5	6	6	9	8	8	6	9	8	6	9	5	9	10	11	7	9	8	6
	5	6	8	6	9	8	9	8	10	8	8	9	5	11	11	11	9	10	8	6
	5	6	9	9	9	9	11	9	10	8	9	11	5	11	11	11	9	10	9	8
	6	6	9	11	11	11	11	9	11	8	9	11	10	11	11	11	9	11	9	8
	9	8	11	11	11	11	11	9	11	9	10	11	11	11	11	11	9	11	10	8
	9	9	11	11	11	11	11	11	11	9	11	11	11	11	11	11	10	11	11	9
	11	9	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11
	11	9	11	11	11	11	11	14	11	11	11	11	11	11	11	11	11	11	11	11
	11	11	11	11	11	11	14	14	11	11	11	14	11	11	11	14	12	14	11	11
	11	14	11	12	12	13	14	15	14	14	11	14	11	14	13	14	14	14	11	11
	11	14	13	14	13	15	14	15	15	14	14	14	14	14	14	15	15	15	14	14
Same Row	2	4	3	1	5	4	3	4	3	7	4	5	1	2	5	2	5	6	6	4
Top Row	3	5	0	2	1	1	1	5	2	3	1	1	3	4	1	2	3	3	3	3
Bottom Row	0	2	1	1	1	2	3	4	2	2	1	3	1	2	2	3	2	3	1	1
X	5	11	4	4	7	7	7	13	7	12	6	9	5	8	8	7	10	12	10	8
	15	9	16	16	13	13	13	7	13	8	14	11	15	12	12	13	10	8	10	12
	15	9	16	16	13	13	13	7	13	8	14	11	15	12	12	13	10	8	10	12
Y	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20

30%

	1	2	3	4	5
35 M1	6	7	8	9	**10**
20 M2	11	12	13	14	15

	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
	1	1	1	1	1	1	1	4	1	1	1	1	1	5	1	1	1	1	1	1
	1	1	2	1	1	1	1	4	1	1	1	1	1	6	1	1	1	1	1	1
	1	1	4	5	1	1	4	5	1	1	1	1	2	8	1	1	5	1	1	1
	2	5	5	5	1	1	5	5	5	1	4	4	2	8	4	1	5	5	1	1
	2	5	5	5	5	2	5	5	5	5	4	5	4	8	4	5	5	5	5	1
	4	8	5	5	5	5	5	6	5	5	5	8	5	8	4	8	5	5	5	1
	5	9	8	5	5	7	8	7	5	5	5	8	5	8	5	8	5	5	5	2
	6	9	8	5	6	8	8	8	6	8	6	8	5	9	5	8	5	5	5	5
	8	9	8	8	8	8	8	8	8	8	9	8	6	9	5	8	8	6	5	5
	8	9	8	8	8	8	8	8	8	9	9	8	8	9	5	8	8	8	5	5
	9	9	8	8	8	8	9	9	9	9	9	8	8	9	5	8	8	8	8	8
	9	9	9	9	9	8	9	9	9	9	9	8	8	9	8	8	9	11	9	8
	9	9	11	9	9	9	11	9	11	11	11	9	8	11	8	9	9	11	9	8
	9	11	11	11	9	9	11	9	11	11	11	9	11	11	9	11	11	11	10	11
	11	11	11	11	11	9	11	11	11	11	11	11	11	11	11	11	11	11	11	11
	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11
	11	11	11	14	14	11	11	14	11	11	11	11	11	12	11	14	11	11	11	11
	11	11	13	14	14	11	14	15	11	14	11	13	14	13	13	14	14	14	11	11
	12	11	14	15	15	14	15	15	11	15	14	15	14	14	14	15	14	14	13	11
Same Row	6	8	6	5	5	8	6	7	4	5	4	9	4	10	3	8	5	2	4	3
Top Row	2	2	4	6	3	1	4	5	4	3	4	2	4	1	8	1	6	5	6	3
Bottom Row	0	0	2	3	3	1	2	3	0	2	1	2	2	2	2	3	2	2	1	0
X	8	10	12	14	11	10	12	15	8	10	9	13	10	13	13	12	13	9	11	6
	12	10	8	6	9	10	8	5	12	10	11	7	10	7	7	8	7	11	9	14
	12	10	8	6	9	10	8	5	12	10	11	7	10	7	7	8	7	11	9	14

Y	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20

35%

	1	2	3	4	5
35 M1	6	7	8	9	**10**
20 M2	11	12	13	14	15

	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
	1	1	1	1	2	1	1	1	4	1	1	1	1	1	1	1	2	1	1	1
	1	4	1	1	4	1	1	4	5	4	1	1	1	5	1	4	2	1	1	1
	4	4	1	1	5	2	1	5	5	5	1	4	1	5	1	4	4	1	4	4
	5	5	2	1	5	2	4	5	5	5	5	4	1	5	1	4	5	1	5	4
	6	5	4	4	5	5	4	6	5	5	5	5	5	5	1	8	5	5	5	5
	7	5	4	5	5	8	4	6	6	6	5	8	5	5	1	8	5	5	6	5
	7	5	5	5	6	8	5	8	6	6	7	8	5	5	5	8	5	5	7	5
	8	8	6	5	7	8	5	8	8	8	8	8	8	6	5	8	7	5	8	5
	8	8	6	6	8	8	5	9	8	8	8	8	8	8	5	8	8	8	8	6
	8	8	7	8	8	8	5	9	8	8	8	8	8	8	5	8	8	8	8	6
	9	8	8	8	8	8	8	10	8	8	8	9	8	8	6	8	8	8	8	6
	9	8	8	8	9	9	10	11	8	9	8	9	8	8	8	9	8	8	8	8
	9	8	9	9	9	11	10	11	8	9	8	11	8	8	9	9	8	9	9	8
	11	8	10	11	9	11	11	11	9	9	8	11	8	8	9	9	8	9	9	9
	11	8	10	11	9	11	11	11	9	10	8	11	9	11	10	11	8	11	9	9
	11	8	11	11	9	11	11	11	11	11	9	15	9	11	11	11	9	11	11	11
	11	9	11	11	10	11	11	13	11	12	9	15	11	11	11	11	9	11	11	12
	11	15	12	13	14	14	11	15	11	15	11	15	15	11	12	15	9	15	14	15
Same Row	6	10	5	4	9	7	3	5	8	8	10	7	9	6	4	10	10	6	8	4
Top Row	2	6	3	4	5	1	7	3	5	4	3	3	3	6	4	3	5	4	3	6
Bottom Row	0	1	0	1	1	1	0	2	0	1	0	3	1	0	0	1	0	1	1	1
X	8	17	8	9	15	9	10	10	13	13	13	13	13	12	8	14	15	11	12	11
	12	3	12	11	5	11	10	10	7	7	7	7	7	8	12	6	5	9	8	9
	12	3	12	11	5	11	10	10	7	7	7	7	7	8	12	6	5	9	8	9
Y	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20

40%

	1	2	3	4	5
35 M1	6	7	8	9	**10**
20 M2	11	12	13	14	15

	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
	1	1	1	1	1	1	1	1	5	1	1	1	1	1	1	1	1	1	1	1
	1	1	1	1	1	1	1	4	5	1	1	1	1	1	1	1	1	1	1	1
	1	1	1	1	1	5	4	4	5	1	1	1	1	1	4	1	1	1	1	1
	1	1	1	1	1	5	4	5	5	1	1	1	1	2	5	5	2	1	1	1
	1	5	1	1	1	5	5	5	5	1	5	5	1	6	5	5	4	4	1	4
	5	5	1	2	4	5	5	5	5	5	5	5	1	6	5	5	4	4	5	5
	5	5	5	4	5	5	5	5	5	5	5	5	1	6	5	5	5	5	5	5
	5	5	6	5	5	8	5	5	5	5	5	5	1	6	5	5	5	5	5	5
	5	6	8	5	5	8	8	6	7	8	5	8	5	8	5	7	5	5	5	5
	5	7	8	5	5	9	8	8	8	8	5	8	5	8	8	8	5	5	5	7
	9	7	8	5	8	9	8	8	8	8	5	8	5	8	8	8	6	8	6	8
	9	8	9	5	8	9	8	8	8	8	5	9	6	8	8	8	8	8	8	8
	9	8	9	8	8	9	9	9	9	8	8	9	8	8	8	8	8	8	8	8
	9	9	9	8	8	10	9	11	9	8	8	9	8	8	8	9	8	8	8	8
	10	9	10	8	8	11	9	11	10	9	8	9	8	9	8	9	8	8	9	9
	11	9	11	8	8	11	9	11	11	9	8	9	9	9	8	11	9	10	9	9
	11	11	11	8	9	11	9	12	11	9	9	9	11	11	8	11	10	11	11	10
	11	11	11	11	11	11	10	14	13	10	11	9	11	11	10	11	11	11	11	11
	11	11	11	14	11	14	14	14	14	11	11	11	13	12	11	11	14	15	11	11
Same Row	5	5	7	5	7	7	10	4	6	10	5	10	4	8	9	6	6	6	5	7
Top Row	5	4	1	6	5	5	6	7	8	3	8	4	3	0	7	5	6	6	5	5
Bottom Row	0	0	0	1	0	1	1	2	2	0	0	0	1	0	0	0	1	1	0	0
X	10	9	8	12	12	13	17	13	16	13	13	14	8	8	16	11	13	13	10	12
	10	11	12	8	8	7	3	7	4	7	7	6	12	12	4	9	7	7	10	8
	10	11	12	8	8	7	3	7	4	7	7	6	12	12	4	9	7	7	10	8
Y	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20

45%

	1	2	3	4	5
35 M1	6	7	8	9	**10**
20 M2	11	12	13	14	15

	1	1	1	1	1	1	1	1	*1*	1	1	1	1	1	1	1	1	1	1	1
	1	1	1	1	1	1	1	2	*1*	1	1	1	1	1	1	1	1	1	1	1
	1	1	1	2	1	1	1	5	5	1	1	1	1	1	4	1	1	1	1	3
	1	5	1	5	1	5	1	5	5	1	5	2	1	1	5	4	1	1	1	4
	2	5	2	5	1	5	1	5	8	1	5	5	2	2	5	5	1	2	1	4
	5	5	4	5	1	5	2	5	8	5	5	5	5	5	5	5	1	5	2	4
	5	6	4	5	5	5	4	5	8	5	5	5	5	6	5	5	1	5	4	5
	5	7	4	8	8	5	5	8	8	5	6	5	8	8	5	5	1	6	5	5
	5	8	5	8	8	8	8	8	8	5	8	5	8	8	7	5	4	8	5	5
	5	8	5	8	8	8	8	8	8	7	8	5	8	8	8	5	5	8	5	5
	6	8	6	8	9	9	10	9	9	8	8	5	8	8	8	6	5	8	8	5
	8	9	8	9	9	9	10	9	9	8	8	6	9	8	9	8	6	8	8	5
	8	9	8	10	9	10	10	9	9	8	8	6	9	8	10	8	8	10	8	8
	8	10	9	10	10	10	11	9	10	8	8	8	10	9	11	9	8	11	9	9
	8	11	10	11	10	10	11	9	10	9	8	8	11	9	11	9	8	11	9	10
	8	14	11	11	10	10	11	9	10	9	10	8	11	11	11	9	8	11	10	10
	8	14	11	11	11	11	11	9	10	11	11	8	11	11	14	10	9	11	11	10
	9	14	11	11	11	11	11	10	*11*	11	11	8	11	11	14	10	11	14	11	10
	11	14	14	11	13	11	11	11	14	11	11	8	13	13	14	11	11	14	14	10
	11	14	14	14	14	14	14	14	14	14	14	14	14	14	14	14	15	14	14	14
Same Row	7	6	4	7	9	8	5	11	13	6	8	6	7	8	4	7	5	5	6	7
Top Row	5	3	5	4	1	5	2	5	2	4	4	7	2	1	6	7	3	2	4	10
Bottom Row	0	5	2	1	2	1	1	1	2	1	1	1	2	2	4	1	1	3	2	1
X	12	14	11	12	12	14	8	17	17	11	13	14	11	11	14	15	9	10	12	18
	8	6	9	8	8	6	12	3	3	9	7	6	9	9	6	5	11	10	8	2

	8	6	9	8	8	6	12	3	3	9	7	6	9	9	6	5	11	10	8	2
Y	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20

50%

		1	2	3	4	5
35,20	M1	6	7	8	9	**10**
	M2	11	12	13	14	15

M1
M2

	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	1	1
	1	1	1	1	1	1	1	1	1	1	1	3	1	3	1	1	1	3	5	1
	1	1	1	1	1	1	1	1	1	2	3	3	2	5	1	1	1	3	5	1
	5	1	3	3	1	1	1	3	1	5	3	4	3	5	1	2	1	5	5	1
	5	1	5	5	1	4	1	3	1	5	4	4	5	5	3	2	1	5	6	4
	5	1	6	5	2	5	5	3	2	6	4	4	5	5	3	2	5	5	6	5
	5	1	6	5	5	5	5	4	5	6	5	5	5	5	4	5	5	6	8	5
	5	5	6	5	5	6	5	4	5	6	6	5	5	5	5	5	5	6	9	6
	6	5	6	5	6	6	5	5	5	10	6	5	5	6	6	5	6	6	9	8
	6	5	9	5	6	6	5	5	5	10	9	5	6	6	8	5	6	6	10	8
	8	5	10	6	9	8	6	6	8	10	9	6	6	8	9	6	6	6	10	9
	9	6	11	6	9	9	6	6	10	10	9	6	6	9	10	6	9	6	11	9
	9	6	11	9	9	9	6	8	10	11	10	9	9	9	10	6	11	9	11	9
	11	9	11	9	9	11	6	10	13	11	10	11	10	10	12	6	11	10	11	9
	11	10	11	9	9	11	6	10	13	11	11	13	10	10	12	8	13	13	11	9
	13	10	12	10	10	11	9	11	13	11	12	13	11	10	13	8	13	13	12	10
	13	13	13	11	13	13	10	13	13	11	13	13	11	11	13	11	13	13	13	11
	13	13	13	11	13	13	11	13	13	11	13	13	11	13	13	13	13	13	13	11
	13	13	13	13	13	13	13	13	13	13	13	13	13	13	13	13	13	13	13	11
	13	13	15	13	13	13	13	13	15	13	13	13	13	13	13	15	15	15	13	13
Same Row	3	3	2	4	6	3	2	3	3	4	5	1	3	6	4	2	1	2	5	8
Top Row	5	4	2	7	2	3	5	7	4	2	5	9	6	7	4	4	3	5	3	3
Bottom Row	5	4	4	2	4	4	2	4	7	2	4	6	2	3	5	3	6	6	4	1
X	13	11	8	13	12	10	9	14	14	8	14	16	11	16	13	9	10	13	12	12
	7	9	12	7	8	10	11	6	6	12	6	4	9	4	7	11	10	7	8	8
	7	9	12	7	8	10	11	6	6	12	6	4	9	4	7	11	10	7	8	8
Y	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20

55%

		1	2	3	4	5
35	M1	6	7	8	9	**10**
20	M2	11	12	13	14	15

	0.01	0.02	0.03	0.04	0.05	0.06	0.07	0.08	0.09	0.1	0.11	0.12	0.13	0.14	0.15	0.16	0.17	0.18	0.19	0.2
	3	1	1	1	1	1	*1*	1	3	1	3	1	1	1	2	1	1	2	1	1
	3	3	3	1	1	3	3	1	3	1	3	1	1	1	3	1	3	3	1	1
	3	3	3	2	2	3	3	1	3	2	3	3	1	1	3	3	3	3	3	2
	3	3	3	3	3	3	5	2	5	3	5	3	3	1	5	6	3	3	3	3
	3	3	3	3	3	3	5	3	5	3	5	3	3	3	5	6	5	3	3	3
	3	3	3	3	3	3	5	5	5	5	5	3	3	3	5	8	5	3	3	3
	5	5	5	3	3	3	9	5	6	5	5	3	5	5	5	8	5	3	3	3
	6	5	5	5	3	3	9	5	6	5	5	3	5	5	5	10	5	5	5	5
	6	5	5	5	3	3	9	5	6	5	6	5	5	5	5	10	5	5	6	5
	9	5	5	5	5	3	10	5	8	5	6	5	5	6	5	10	6	6	6	8
	9	5	5	5	5	3	10	5	9	5	10	5	5	9	6	10	6	6	9	9
	9	5	6	5	5	3	10	5	9	6	10	5	5	10	8	10	9	6	9	10
	9	9	6	5	6	5	10	6	9	9	10	5	5	10	9	10	9	9	10	12
	9	10	8	6	6	5	10	9	9	10	10	9	6	10	9	13	9	10	10	13
	9	10	9	6	10	5	10	10	9	10	10	9	9	12	9	13	10	10	10	13
	10	10	10	10	10	5	13	12	11	10	12	10	9	13	13	13	10	12	13	13
	10	13	10	11	10	5	13	12	13	10	13	10	9	13	13	13	10	13	13	13
	10	13	10	12	10	10	13	13	13	10	13	13	9	13	13	13	10	13	13	13
	13	13	13	13	13	10	13	13	13	13	13	13	13	13	13	13	12	13	13	13
	13	13	13	13	13	11	13	13	13	13	13	13	15	15	13	13	13	15	15	13
Same Row	9	4	5	1	4	2	9	2	6	6	5	4	4	4	4	8	7	3	5	3
Top Row	6	11	10	10	9	16	5	8	5	8	7	11	10	5	9	1	8	8	6	6
Bottom Row	2	4	2	2	2	0	5	3	4	2	4	3	2	5	5	7	1	4	5	7
X	17	19	17	13	15	18	19	13	15	16	16	18	16	14	18	16	16	15	16	16
	2	1	3	7	5	2	1	7	4	4	3	2	4	6	2	4	4	5	4	4
	2	1	3	7	5	2	1	7	4	4	3	2	4	6	2	4	4	5	4	4
Y	19	20	20	20	20	20	20	20	19	20	19	20	20	20	20	20	20	20	20	20

60%

		1	2	3	4	5
32	M1	6	7	8	9	**10**
18	M2	11	12	13	14	15

	1	1	2	1	1	2	2	2	1	2	1	1	2	2	2	2	1	1	3	2
	1	2	3	2	2	2	2	3	2	2	2	1	5	2	2	2	2	3	4	2
	2	3	3	2	2	3	2	4	3	2	3	1	5	2	3	2	2	4	5	2
	2	3	5	2	2	4	3	5	4	2	3	2	5	2	3	2	3	5	5	2
	2	3	6	3	2	5	3	5	4	2	4	3	5	3	3	2	3	5	5	2
	2	4	6	5	2	5	3	5	5	2	5	5	5	3	3	3	3	5	5	3
	3	4	9	5	3	5	4	5	5	3	5	5	5	3	5	3	3	5	5	3
	3	5	9	5	5	5	5	5	9	5	5	5	9	4	5	3	5	5	9	3
	3	5	10	9	5	6	5	5	9	5	6	6	10	5	9	5	5	9	9	4
	3	5	10	9	5	10	5	5	9	5	6	9	10	5	9	5	5	9	9	5
	5	5	10	9	5	10	5	6	10	5	9	9	10	9	9	6	5	10	10	5
	5	5	10	9	9	10	9	9	10	5	9	9	10	10	10	10	9	10	10	5
	5	5	13	10	9	13	10	10	10	9	10	9	13	10	10	10	9	10	10	5
	5	6	13	10	10	13	10	10	10	9	10	10	13	10	10	13	9	10	10	6
	10	9	13	10	13	13	10	10	10	9	10	10	13	15	13	13	10	10	10	9
	10	13	13	13	13	13	13	10	10	10	10	13	13	15	13	13	10	13	13	9
	13	15	15	13	13	13	13	10	13	10	10	13	13	15	15	13	13	13	13	9
	13	15	15	13	15	15	15	10	13	10	13	13	15	15	15	13	15	15	15	10
	15	15	15	13	15	15	15	10	13	13	15	15	15	15	15	15	15	15	15	15
	15	15	15	15	15	15	15	13	15	15	15	15	15	15	15	15	15	15	15	15
Same Row	2	1	6	7	3	3	4	8	9	6	7	6	5	4	6	2	5	7	8	4
Top Row	8	11	3	4	5	6	8	9	5	6	6	4	6	6	6	5	8	7	7	8
Bottom Row	4	5	8	5	6	8	5	1	4	2	3	5	8	6	6	7	4	5	5	2
X	14	17	17	16	14	17	17	18	18	14	16	15	19	16	18	14	17	19	20	14

	6	3	3	4	6	3	3	2	2	6	4	5	1	4	2	6	3	1	0	6
	6	3	3	4	6	3	3	2	2	6	4	5	1	4	2	6	3	1	0	6
Y	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20

65%

	1	2	3	4	5
35 M1	6	7	8	9	**10**
20 M2	11	12	13	14	15

	2	2	3	3	2	2	2	3	2	3	2	3	2	2	2	2	2	2	3	2
	3	3	3	3	2	2	3	4	3	3	3	3	2	3	2	3	2	2	3	2
	3	3	3	3	3	3	3	4	3	3	3	3	2	3	3	3	3	2	3	3
	4	3	4	4	3	3	3	4	5	3	3	3	3	3	3	3	3	3	3	3
	5	3	5	5	3	3	5	4	5	5	5	5	3	3	3	3	3	3	3	3
	5	5	5	5	3	3	5	4	5	5	5	5	3	3	4	3	3	3	5	3
	9	5	5	5	3	3	5	5	5	9	5	5	3	4	4	3	3	3	5	5
	9	5	5	9	3	3	5	5	6	9	5	5	3	5	5	5	5	3	5	5
	10	6	5	9	3	3	5	5	9	9	5	5	3	6	5	5	5	3	9	5
	10	9	5	9	5	3	6	5	10	9	5	6	5	10	5	5	5	6	10	5
	10	10	5	9	9	3	9	6	10	10	10	6	5	10	5	5	5	6	10	5
	10	10	6	9	9	3	10	9	10	10	10	9	9	10	5	9	5	9	10	6
	10	10	9	10	10	3	10	9	10	10	10	9	10	10	6	10	5	9	10	10
	10	10	9	10	10	3	10	9	10	10	10	10	10	10	9	10	5	9	13	10
	10	10	10	10	10	5	13	10	13	15	10	10	10	10	10	10	9	10	13	10
	13	10	13	10	10	9	13	10	13	15	13	10	10	10	10	13	9	10	13	10
	13	13	13	13	10	9	13	13	13	15	13	13	10	13	10	13	10	10	13	13
	14	13	13	13	13	10	13	13	13	15	14	15	13	13	10	14	10	13	13	13
	15	15	14	13	15	13	15	15	15	15	15	15	13	15	13	15	10	13	15	14
	15	15	15	15	15	13	15	15	15	15	15	15	13	15	13	15	10	15	15	15

Same Row	9	7	3	9	7	3	4	5	6	8	5	5	6	7	5	4	6	6	5	4
Top Row	5	7	11	7	8	13	8	10	6	6	9	9	8	7	10	10	12	6	8	9
Bottom Row	5	4	5	4	3	2	6	4	6	6	5	4	3	4	2	5	0	3	7	4
X	19	18	19	20	18	18	18	19	18	20	19	18	17	18	17	19	18	15	20	17
	1	2	1	0	2	2	2	1	2	0	1	2	3	2	3	1	2	5	0	3
	1	2	1	0	2	2	2	1	2	0	1	2	3	2	3	1	2	5	0	3
Y	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20

70%

	1	2	3	4	5
35 M1	6	7	8	9	**10**
20 M2	11	12	13	14	15

	3	3	3	3	3	3	2	3	3	2	3	3	3	3	4	2	2	3	2	3
	3	3	3	3	3	3	3	3	3	3	3	3	3	3	4	3	3	3	3	3
	3	3	3	3	3	3	3	3	3	3	3	3	3	3	4	3	3	3	3	4
	3	3	3	3	3	3	4	4	3	3	3	5	3	4	5	5	3	3	3	5
	3	3	3	3	4	5	4	5	3	3	3	5	4	4	5	5	3	3	3	5
	3	4	4	3	4	5	5	5	4	3	4	5	5	4	5	9	5	3	4	5
	4	4	5	3	5	5	5	5	4	5	5	5	5	5	5	9	9	5	5	5
	5	5	5	4	5	6	5	5	5	6	5	5	5	5	9	9	9	5	5	10
	5	9	5	5	5	9	5	9	5	9	5	10	5	5	10	10	10	9	5	10
	5	9	9	5	5	10	5	9	5	9	5	10	9	5	10	10	10	9	5	10
	9	10	10	6	5	10	5	10	5	10	5	10	10	5	10	10	10	10	5	10
	9	10	10	10	6	10	9	10	9	10	9	10	10	5	10	10	13	10	9	10
	10	10	10	10	9	13	10	10	10	10	10	10	10	9	13	10	13	10	10	10
	10	10	10	10	9	13	10	10	10	10	10	10	10	10	13	10	13	13	10	10
	10	10	10	10	9	13	10	13	10	13	10	10	10	10	13	10	13	13	13	10
	10	10	13	13	10	13	10	14	13	13	10	13	10	10	15	13	13	13	13	10
	13	13	15	13	13	15	13	15	13	13	10	13	13	10	15	13	15	13	13	10
	13	15	15	13	13	15	13	15	15	15	14	15	13	13	15	13	15	15	15	15
	15	15	15	15	15	15	13	15	15	15	15	15	13	14	15	15	15	15	15	15
	15	15	15	15	15	15	13	15	15	15	15	15	13	15	15	15	15	15	15	15

Same Row	6	8	6	4	4	4	5	6	4	6	6	7	7	5	5	10	5	5	3	10
Top Row	10	8	9	10	11	7	10	8	11	6	11	8	9	12	7	4	5	8	10	7
Bottom Row	4	4	5	5	4	8	4	6	5	6	3	5	4	3	8	5	9	7	6	3
X	20	20	20	19	19	19	19	20	20	18	20	20	20	20	20	19	19	20	19	20
	0	0	0	1	1	1	1	0	0	2	0	0	0	0	0	1	1	0	1	0
	0	0	0	1	1	1	1	0	0	2	0	0	0	0	0	1	1	0	1	0
Y	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20

75%

	1	2	3	4	5
35 M1	6	7	8	9	**10**
20 M2	11	12	13	14	15

	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
	3	3	3	3	3	3	3	3	5	3	3	3	3	3	3	3	3	3	3	5
	3	3	3	3	3	3	5	3	5	3	5	3	3	3	3	3	4	3	4	5
	4	3	3	3	5	3	5	3	9	3	6	3	3	5	4	3	5	3	5	5
	4	3	5	3	5	3	5	3	9	5	6	3	5	5	4	4	9	3	5	9
	4	4	5	3	5	4	9	5	10	9	9	3	5	5	5	4	9	3	5	9
	5	4	5	5	10	5	9	5	10	9	10	5	5	9	5	5	9	3	5	10
	5	5	5	5	10	5	10	5	10	9	10	5	6	10	5	5	10	5	5	10
	5	5	6	5	10	5	10	5	10	10	10	5	10	10	5	5	10	5	5	10
	10	5	9	5	10	5	10	9	10	10	10	5	10	10	9	10	10	5	5	10
	10	5	10	6	10	5	10	10	10	10	10	5	10	10	9	10	10	5	9	10
	10	9	10	9	10	10	10	10	13	10	10	5	10	10	10	10	10	9	10	10
	10	10	10	10	10	10	10	10	13	10	10	9	10	10	10	10	10	10	10	10
	13	10	10	10	10	10	10	10	14	10	10	10	10	13	10	10	10	10	10	10
	13	10	10	10	10	10	10	10	15	10	10	10	10	14	10	10	10	10	13	10
	13	10	10	10	13	10	13	10	15	10	13	10	13	15	10	10	10	10	13	13
	13	13	10	14	13	10	13	13	15	14	13	10	13	15	10	13	10	10	13	13
	14	13	13	14	14	10	13	13	15	14	13	10	14	15	13	15	13	14	15	14
	14	15	14	15	15	10	13	13	15	14	15	14	15	15	15	15	13	14	15	15
	15	15	14	15	15	13	15	15	15	15	15	15	15	15	15	15	13	15	15	15

Same Row	4	5	8	5	9	8	10	7	8	11	10	6	7	7	8	7	13	6	4	11
Top Row	9	11	8	10	6	11	5	9	3	5	3	12	7	6	9	9	4	11	10	4
Bottom Row	7	4	3	4	5	1	5	4	9	4	5	2	5	7	3	4	3	3	6	5

X	20	20	19	19	20	20	20	20	20	20	18	20	19	20	20	20	20	20	20	20
	0	0	1	1	0	0	0	0	0	0	2	0	1	0	0	0	0	0	0	0
	0	0	1	1	0	0	0	0	0	0	2	0	1	0	0	0	0	0	0	0
Y	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20

80%

	1	2	3	4	5
35 M1	6	7	8	9	**10**
20 M2	11	12	13	14	15

5	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
5	3	3	5	3	3	3	3	5	3	3	5	3	3	3	3	3	3	3	3
5	4	3	5	3	3	5	4	5	3	3	5	3	3	3	3	3	3	3	5
5	5	3	5	4	3	5	5	5	3	5	5	3	4	3	3	3	5	5	5
5	5	5	9	5	4	5	5	5	3	5	5	3	5	3	5	3	5	5	5
5	9	5	9	5	5	5	5	5	4	5	5	3	5	3	5	3	5	5	5
5	10	5	10	5	5	5	9	5	4	5	9	5	5	3	9	3	5	5	5
5	10	5	10	9	9	5	9	10	5	5	10	5	5	4	10	5	5	10	5
5	10	9	10	10	10	9	10	10	5	9	10	9	5	5	10	5	5	10	5
5	10	9	10	10	10	10	10	10	5	10	10	10	5	9	10	5	5	10	5
9	10	10	10	10	10	10	10	10	9	10	10	10	9	10	10	5	10	10	10
10	10	10	10	10	10	10	10	10	10	10	10	10	9	10	10	9	10	10	10
10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
10	13	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
10	13	10	10	10	10	10	13	10	10	10	10	13	10	13	10	10	10	10	10
10	13	10	10	13	10	13	13	10	10	10	10	13	10	13	13	10	10	10	10
10	13	13	13	13	10	13	14	13	11	10	13	13	13	14	13	13	13	13	13
10	14	15	14	15	13	14	15	13	13	13	13	14	15	14	13	14	15	13	13
10	15	15	14	15	15	15	15	14	13	15	14	14	15	14	13	14	15	15	15

Same Row	10	9	9	13	9	11	8	9	10	7	10	11	7	7	6	10	6	7	10	7
Top Row	10	5	8	4	7	7	8	6	7	10	8	6	8	10	9	6	11	10	7	10
Bottom Row	0	6	3	3	4	2	4	5	3	2	2	3	5	3	5	4	3	3	3	3

X	20	20	20	20	20	20	20	20	20	19	20	20	20	20	20	20	20	20	20	20
	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
Y	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20

85%

	1	2	3	4	5
35 M1	6	7	8	9	**10**
20 M2	11	12	13	14	15

5	3	3	3	3	4	5	3	3	3	3	3	3	5	3	5	5	3	5	3
5	3	3	5	4	5	10	5	5	3	5	5	3	5	3	5	5	3	5	3
5	3	3	9	5	5	10	5	5	3	5	5	3	9	5	9	5	3	5	3
5	3	3	9	5	5	10	5	5	5	5	5	5	9	5	10	9	3	5	3
9	3	3	10	5	5	10	5	5	5	9	5	5	9	9	10	9	3	9	4
9	4	5	10	5	9	10	5	9	5	10	9	5	9	9	10	9	5	9	5
9	5	5	10	5	9	10	9	9	9	10	9	5	9	9	10	9	5	10	5
10	5	5	10	9	10	10	9	9	9	10	10	10	10	10	10	9	5	10	5
10	5	9	10	9	10	10	10	10	10	10	10	10	10	10	10	10	9	10	5
10	5	9	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
10	9	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
10	9	10	13	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
10	10	10	13	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
10	10	10	13	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
10	10	10	13	10	13	10	10	10	10	13	10	10	10	10	10	10	10	11	10
10	10	10	13	10	13	13	10	10	10	13	11	10	10	10	13	10	10	13	10
13	10	10	13	13	13	13	13	10	10	14	13	13	10	10	13	10	10	13	10
13	10	11	13	14	13	14	13	10	13	14	13	13	11	13	13	10	10	13	13
13	13	13	14	14	14	14	13	10	13	14	14	14	13	14	14	13	13	13	13
14	13	13	15	15	14	15	13	13	14	15	15	14	13	15	15	13	14	14	14

Same Row	12	8	9	9	9	9	14	10	14	11	10	10	9	15	13	13	15	10	10	8
Top Row	4	10	8	2	7	5	1	6	5	6	4	5	7	2	4	2	3	8	4	9
Bottom Row	4	2	2	9	4	6	5	4	1	3	6	4	4	2	3	5	2	2	5	3

X	20	20	19	20	20	20	20	20	20	20	20	19	20	19	20	20	20	20	19	20
	0	0	1	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	1	0
	0	0	1	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	1	0
Y	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20

90%

	1	2	3	4	5
35 M1	6	7	8	9	**10**
20 M2	11	12	13	14	15

3	5	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
5	5	3	3	3	4	5	3	3	3	3	3	3	3	3	3	3	3	3	3
5	5	3	3	5	5	5	3	3	3	3	5	3	3	5	3	3	5	3	5
5	5	5	3	5	5	5	5	3	3	3	5	5	5	5	3	5	5	3	5
5	5	5	5	5	5	5	5	5	5	3	5	5	5	5	3	5	5	4	5
10	9	5	5	5	9	10	5	5	5	5	5	9	5	5	5	9	9	5	5
10	10	9	5	5	10	10	9	5	5	5	5	10	5	9	5	9	9	5	5
10	10	9	5	5	10	10	9	5	5	5	5	10	5	9	9	9	10	10	5
10	10	9	5	9	10	10	10	5	5	5	9	10	10	10	9	10	10	10	9
10	10	10	9	9	10	10	10	5	9	5	10	10	10	10	10	10	10	10	10
10	10	10	10	9	10	10	10	5	10	9	10	10	10	10	10	10	10	10	10
10	10	10	10	10	10	10	10	9	10	9	10	10	10	10	10	10	10	10	10
10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	13	10	10
10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	13	10	10
13	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	13	10	10
13	10	10	10	10	10	10	10	10	10	10	10	10	13	10	13	10	13	10	10
13	10	10	10	10	10	10	10	10	10	10	13	10	13	10	13	10	13	10	13
13	10	10	10	13	10	10	10	10	10	10	13	13	13	10	13	10	15	10	13
13	13	13	13	14	10	13	13	13	13	13	14	13	13	13	13	13	15	13	13
15	13	14	13	15	13	15	15	13	13	15	15	13	15	15	13	15	15	13	13

Same Row	9	13	12	9	9	14	13	12	7	9	8	8	12	7	12	8	13	7	11	8
Top Row	5	5	6	9	8	5	5	6	11	9	10	8	5	8	6	7	5	5	7	8

Bottom Row	6	2	2	2	3	1	2	2	2	2	2	4	3	5	2	5	2	8	2	4
X	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20
	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Y	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20

A.2.1.5 CS1 Additional ProMps Results

10%

35 M1

20 M2

1	2	3	**4**	5
6	7	8	9	10
11	12	13	14	15

User 1019 Cell 4 Predictions

1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
1	1	5	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
1	1	5	1	1	1	1	1	1	1	1	1	1	1	2	1	1	2	1	1
1	1	5	1	1	2	1	1	1	1	1	2	1	1	4	1	1	2	1	1
1	1	5	1	2	4	4	1	1	2	1	2	2	1	5	1	1	4	1	1
1	1	5	2	5	5	4	1	1	4	1	5	2	1	5	1	1	5	1	1
1	5	5	2	5	6	5	1	4	4	1	5	2	1	5	1	4	5	1	1
1	5	5	4	11	8	5	4	4	5	5	5	5	1	5	4	4	5	1	4
1	5	6	4	11	8	5	4	5	5	5	8	5	2	5	4	5	6	2	5
2	5	6	5	11	8	5	5	5	5	5	8	5	5	5	4	5	8	5	5
4	8	8	5	11	9	5	5	5	5	5	8	6	5	5	5	8	11	5	5
5	11	9	5	11	11	6	5	5	8	8	8	8	5	11	5	11	11	5	5
8	11	11	11	11	11	8	5	5	9	11	8	11	5	11	5	11	11	5	11
8	11	11	11	11	11	11	11	8	11	11	11	11	8	11	11	11	11	5	11
11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	5	11
11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11
11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11
11	11	11	11	11	11	11	11	11	11	14	11	11	11	11	11	11	11	11	11
11	14	11	11	11	11	11	11	11	11	14	11	11	11	14	11	11	11	11	11
14	14	14	14	11	14	11	14	11	14	14	11	11	11	14	11	11	11	11	11

2	4	7	5	2	2	7	6	7	6	4	3	3	4	8	6	4	4	6	5
2	1	2	0	0	4	1	0	1	2	1	5	1	1	0	0	1	1	0	0
1	2	1	1	0	1	0	1	0	1	3	0	0	0	2	0	0	0	0	0

X	5	7	10	6	2	7	8	7	8	9	8	8	4	5	10	6	5	5	6	5

5	7	7	7	13	8	7	6	6	6	5	7	8	6	7	7	9	10	5	8
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

	5	7	7	7	13	8	7	6	6	6	5	7	8	6	7	7	9	10	5	8
Y	10	14	17	13	15	15	15	13	14	15	13	15	12	11	17	13	14	15	11	13

15%

35 M1

20 M2

1	2	3	**4**	5
6	7	8	9	10
11	12	13	14	15

1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	1	1
1	1	1	1	1	1	1	1	3	1	1	1	1	1	1	1	1	2	1	1

1	1	1	3	1	1	1	1	4	1	1	1	1	1	1	1	1	2	1	1
1	1	2	3	2	1	1	1	5	1	1	1	1	1	1	1	1	2	2	2
1	1	4	5	2	1	2	2	5	2	1	1	1	2	1	1	1	3	2	4
1	4	4	5	5	1	2	3	5	5	1	1	1	4	1	1	2	5	3	5
2	5	5	5	5	2	4	5	5	5	2	4	1	4	2	5	4	5	5	5
4	5	5	6	5	2	5	5	5	5	2	5	3	4	5	5	5	5	5	5
4	5	5	11	5	2	5	5	8	5	3	5	4	4	6	5	5	5	5	5
5	5	11	11	5	3	5	6	9	5	4	5	5	4	6	5	8	8	5	11
5	5	11	11	5	5	5	11	11	5	5	5	5	5	8	5	11	11	5	11
5	5	11	11	8	5	6	11	11	6	5	5	6	5	8	5	11	11	6	11
5	8	11	11	8	6	8	11	11	6	11	5	8	5	11	6	11	11	11	11
5	11	11	11	11	9	8	11	11	8	11	5	9	11	11	11	11	11	11	11
8	11	11	11	11	11	8	11	11	11	11	6	11	11	11	11	11	11	11	11
11	11	14	11	11	11	11	11	11	11	11	6	11	11	11	11	11	11	11	11
11	11	14	11	11	11	11	11	11	11	11	8	11	11	11	11	11	11	11	11
11	11	14	11	11	11	11	11	11	14	11	11	11	11	11	11	11	11	11	11
14	11	14	14	11	14	11	11	14	14	11	11	11	14	14	11	11	11	11	11

7	7	5	5	6	3	5	4	7	6	4	8	4	8	1	6	3	5	6	5
1	1	0	0	2	1	3	0	2	1	0	1	2	0	2	0	1	1	0	0
1	0	4	1	0	1	0	0	1	2	0	0	0	1	1	0	0	0	0	0

X	9	8	9	6	8	5	8	4	10	9	4	9	6	9	4	6	4	6	6	5

3	6	6	10	6	4	4	9	8	3	7	2	5	5	6	6	9	9	7	10
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

	3	6	6	10	6	4	4	9	8	3	7	2	5	5	6	6	9	9	7	10
Y	12	14	15	16	14	9	12	13	18	12	11	11	11	14	10	12	13	15	13	15

20%	1	2	3	**4**	5
35 M1	6	7	8	9	10
20 M2	11	12	13	14	15

1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	2	1	4	1	1	1	1	1	1	1	1	1
1	1	2	1	1	1	1	1	2	5	5	1	1	1	5	1	5	2	1	1
1	1	5	1	2	1	4	1	5	5	5	2	1	2	5	3	5	4	1	1
2	1	5	5	5	1	5	1	5	6	5	4	5	2	5	4	5	5	1	1
2	2	6	5	5	2	5	4	5	8	8	5	5	5	5	5	5	5	1	5
2	2	8	5	5	2	5	5	5	11	11	5	5	5	5	5	5	5	2	5
2	4	8	11	8	2	5	5	5	11	11	5	5	5	5	5	5	8	4	5
4	5	9	11	8	2	6	5	5	11	11	5	8	6	5	8	8	11	5	5

5	5	11	11	9	5	6	5	5	11	11	5	8	11	5	8	8	11	5	5
5	5	11	11	11	8	11	6	11	11	11	9	9	11	5	9	11	11	5	5
11	5	11	11	11	11	11	9	11	11	11	11	9	11	8	11	11	11	5	8
11	5	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	5	11
11	8	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	6	11
11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11
11	11	11	11	11	11	11	11	14	11	11	11	11	11	11	11	11	11	11	11
11	11	11	11	11	14	14	11	14	11	11	11	11	11	11	11	11	11	11	11
11	14	11	11	11	14	14	11	14	11	11	14	14	11	11	14	11	14	11	11

3	6	2	3	3	1	5	5	7	2	4	6	4	3	9	5	6	4	6	6
0	1	3	0	3	1	0	1	0	1	1	1	4	0	1	3	2	1	0	1
0	1	0	0	0	2	2	0	3	0	0	1	1	0	0	1	0	1	0	0

X	3	8	5	3	6	4	7	6	10	3	5	8	9	3	10	9	8	6	6	7

7	3	9	11	8	5	6	6	5	12	12	6	5	9	6	6	8	9	4	6
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

	7	3	9	11	8	5	6	6	5	12	12	6	5	9	6	6	8	9	4	6
Y	10	11	14	14	14	9	13	12	15	15	17	14	14	12	16	15	16	15	10	13

25%	1	2	3	**4**	5
35 M1	6	7	8	9	10
20 M2	11	12	13	14	15

1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
2	1	1	1	1	1	1	2	2	1	1	1	1	1	1	1	1	1	1	1
2	1	1	1	1	1	1	5	5	1	1	1	1	1	1	1	1	1	1	1
5	1	2	2	1	1	1	5	6	1	5	1	1	1	1	2	2	1	1	1
5	1	2	2	1	2	1	5	9	2	5	4	2	1	1	5	5	1	1	1
5	2	5	5	5	5	1	5	9	2	5	5	2	1	1	5	5	2	1	2
5	2	5	5	5	5	2	5	11	5	5	5	4	2	5	5	5	2	1	5
11	5	5	5	9	5	5	11	11	5	5	5	5	5	5	5	5	5	4	5
11	5	5	5	9	6	5	11	11	5	9	5	6	5	5	5	5	5	5	5
11	5	6	5	11	6	6	11	11	5	11	5	6	5	5	5	5	5	5	5
11	11	11	5	11	6	11	11	11	6	11	5	11	5	5	11	9	5	5	5
11	11	11	5	11	9	11	11	11	9	11	9	11	5	9	11	9	11	9	11
11	11	11	9	11	9	11	11	11	9	11	11	11	6	11	11	9	11	9	11
11	11	11	9	11	11	11	11	11	11	11	11	11	9	11	11	11	11	11	11
11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11
11	11	11	11	11	11	11	11	11	11	14	11	11	11	11	11	11	11	11	11
11	11	11	11	11	11	11	11	14	11	14	11	11	11	11	11	11	11	11	11

11	11	14	11	11	14	14	14	14	11	15	14	14	11	14	14	14	11	11	14

4	3	4	7	2	3	2	5	1	4	5	7	2	5	5	6	6	4	4	5
0	0	0	2	2	2	0	0	2	2	1	1	0	1	1	0	3	0	2	0
0	0	1	0	0	1	1	1	2	0	3	1	1	0	1	1	1	0	0	1

X	4	3	5	9	4	6	3	6	5	6	9	9	3	6	7	7	10	4	6	6

11	8	7	4	9	4	7	10	10	5	6	5	7	4	5	7	4	7	5	6
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

	11	8	7	4	9	4	7	10	10	5	6	5	7	4	5	7	4	7	5	6
Y	15	11	12	13	13	10	10	16	15	11	15	14	10	10	12	14	14	11	11	12

30%	1	2	3	**4**	5
35 M1	6	7	8	9	10
20 M2	11	12	13	14	15

1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
5	1	1	1	1	1	1	1	1	1	1	5	1	1	1	1	1	1	1	1
5	1	1	5	1	2	1	1	1	2	1	5	1	1	1	1	1	2	1	1
5	1	1	5	1	5	1	1	1	5	4	5	1	1	1	1	1	5	2	1
5	1	1	5	1	5	2	2	1	5	5	5	2	1	2	1	1	5	5	5
5	2	1	5	1	5	5	5	1	5	5	9	2	2	5	1	5	5	5	5
5	5	5	5	5	5	5	5	5	5	6	9	5	5	5	1	5	9	5	6
5	5	5	5	5	5	5	5	5	5	9	9	5	5	5	1	5	11	5	6
11	5	5	5	5	5	5	9	5	6	9	11	9	5	5	2	5	11	6	11
11	5	6	5	5	9	9	9	5	9	9	11	11	5	5	5	9	11	9	11
11	5	6	5	5	9	11	11	5	9	11	11	11	5	9	6	9	11	11	11
11	9	9	5	5	11	11	11	5	11	11	11	11	9	11	9	11	11	11	11
11	9	11	5	9	11	11	11	5	11	11	11	11	9	11	9	11	11	11	11
11	9	11	5	11	11	11	11	9	11	11	11	11	11	11	11	11	11	11	11
11	11	11	11	11	11	11	11	9	11	11	11	11	11	11	11	11	14	11	11
11	11	11	11	11	11	11	11	9	11	12	11	11	11	11	11	11	14	11	11
11	11	11	11	11	11	14	11	11	12	14	12	11	11	11	11	14	14	14	11
11	11	11	12	11	14	14	11	14	14	14	14	11	14	11	11	14	15	14	14

7	5	3	12	6	6	4	3	7	5	3	4	2	5	5	1	4	3	4	2
0	3	1	0	1	2	1	2	3	2	3	3	1	2	1	2	2	1	1	0
0	0	0	0	0	1	2	0	1	1	2	1	0	1	0	0	2	4	2	1

X	7	8	4	12	7	9	7	5	11	8	8	8	3	8	6	3	8	8	7	3

	10	4	6	3	5	6	6	8	1	5	5	8	9	4	7	5	5	7	6	9
	0	0	0	1	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0
	10	4	6	4	5	6	6	8	1	6	6	9	9	4	7	5	5	7	6	9
Y	17	12	10	16	12	15	13	13	12	14	14	17	12	12	13	8	13	15	13	12

35%

	1	2	3	**4**	5
35 M1	6	7	8	9	10
20 M2	11	12	13	14	15

1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	4	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	4	1	1	2	1	1	1	2	1	1
1	1	1	4	4	1	1	2	1	1	5	1	1	2	1	1	1	4	1	1
1	1	2	4	4	1	4	2	2	1	5	4	2	4	4	1	1	5	4	1
4	4	4	5	5	1	4	4	5	1	5	5	5	5	4	1	1	5	5	2
5	4	5	5	5	2	5	5	5	4	5	5	5	5	5	1	2	5	5	2
5	4	5	5	5	5	5	5	5	4	5	5	5	5	5	4	2	5	5	4
5	4	5	5	5	5	5	5	5	5	5	6	5	5	5	5	4	6	5	5
5	5	5	9	5	5	5	5	5	5	6	9	5	5	5	5	5	11	5	5
9	9	5	9	9	5	5	5	9	5	11	9	5	5	11	5	5	11	9	5
9	9	5	11	9	5	9	5	9	9	11	9	9	9	11	6	5	11	11	9
9	11	5	11	9	9	11	9	9	9	11	9	11	9	11	9	9	11	11	9
11	11	9	11	11	11	11	11	11	9	11	11	11	9	11	9	11	11	11	11
11	11	9	11	11	11	11	11	11	9	11	11	11	9	11	11	11	11	11	11
11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11
11	11	11	11	11	11	12	11	11	11	11	11	11	11	11	11	11	11	11	11
11	11	11	11	11	11	12	11	11	11	11	11	12	11	11	11	11	11	11	11
11	11	11	11	11	11	13	11	11	11	12	11	12	12	11	11	11	12	11	11
12	11	11	11	11	12	13	13	11	11	12	13	12	12	12	12	14	12	11	11

	5	5	8	6	7	5	7	7	5	5	8	4	6	7	6	4	4	5	6	4
	3	2	2	2	3	1	1	1	3	4	0	4	1	4	0	2	1	0	1	2
	0	0	0	0	0	0	2	1	0	0	0	1	0	0	0	0	1	0	0	0
X	8	7	10	8	10	6	10	9	8	9	8	9	7	11	6	6	6	5	7	6

	6	8	5	9	7	6	4	6	7	5	8	6	5	3	9	5	6	9	9	7
	1	0	0	0	0	1	2	0	0	0	2	0	3	2	1	1	0	2	0	0
	7	8	5	9	7	7	6	6	7	5	10	6	8	5	10	6	6	11	9	7
Y	15	15	15	17	17	13	16	15	15	14	18	15	15	16	16	12	12	16	16	13

40%

35 M1

20 M2

1	2	3	**4**	5
6	7	8	9	10
11	12	13	14	15

1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	4	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	4	1	1	2	1	1	1	2	1	1
1	1	1	4	4	1	1	2	1	1	5	1	1	2	1	1	1	4	1	1
1	1	2	4	4	1	4	2	2	1	5	4	2	4	4	1	1	5	4	1
4	4	4	5	5	1	4	4	5	1	5	5	5	5	4	1	1	5	5	2
5	4	5	5	5	2	5	5	5	4	5	5	5	5	5	1	2	5	5	2
5	4	5	5	5	5	5	5	5	4	5	5	5	5	5	4	2	5	5	4
5	4	5	5	5	5	5	5	5	5	5	6	5	5	5	5	4	6	5	5
5	5	5	9	5	5	5	5	5	5	6	9	5	5	5	5	5	11	5	5
9	9	5	9	9	5	5	5	9	5	11	9	5	5	11	5	5	11	9	5
9	9	5	11	9	5	9	5	9	9	11	9	9	9	11	6	5	11	11	9
9	11	5	11	9	9	11	9	9	9	11	9	11	9	11	9	9	11	11	9
11	11	9	11	11	11	11	11	11	9	11	11	11	9	11	9	11	11	11	11
11	11	9	11	11	11	11	11	11	9	11	11	11	9	11	11	11	11	11	11
11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11
11	11	11	11	11	11	12	11	11	11	11	11	11	11	11	11	11	11	11	11
11	11	11	11	11	11	12	11	11	11	11	11	12	11	11	11	11	11	11	11
11	11	11	11	11	11	13	11	11	11	12	11	12	12	11	11	11	12	11	11
12	11	11	11	11	12	13	13	11	11	12	13	12	12	12	12	14	12	11	11

	5	5	8	6	7	5	7	7	5	5	8	4	6	7	6	4	4	5	6	4
	3	2	2	2	3	1	1	1	3	4	0	4	1	4	0	2	1	0	1	2
	0	0	0	0	0	0	2	1	0	0	0	1	0	0	0	0	1	0	0	0
X	8	7	10	8	10	6	10	9	8	9	8	9	7	11	6	6	6	5	7	6
	6	8	5	9	7	6	4	6	7	5	8	6	5	3	9	5	6	9	9	7
	1	0	0	0	0	1	2	0	0	0	2	0	3	2	1	1	0	2	0	0
	7	8	5	9	7	7	6	6	7	5	10	6	8	5	10	6	6	11	9	7
Y	15	15	15	17	17	13	16	15	15	14	18	15	15	16	16	12	12	16	16	13

45%

35 M1

20 M2

1	2	3	**4**	5
6	7	8	9	10
11	12	13	14	15

2	2	2	1	4	4	1	4	1	2	1	3	2	2	2	4	4	1	2	2
4	2	4	2	4	4	4	4	2	4	2	4	2	4	4	4	4	2	2	2
4	4	5	2	4	4	4	4	3	4	2	4	2	4	4	4	4	4	4	4
4	4	5	4	4	4	4	4	4	4	4	4	2	4	4	4	4	4	4	4
4	4	5	4	4	5	4	4	4	4	4	4	4	4	4	4	5	4	4	4
4	4	5	4	4	5	4	4	4	4	4	4	4	4	4	4	5	4	4	5
4	4	5	4	5	5	5	5	4	4	4	4	4	4	5	4	5	4	4	5
5	5	5	4	5	5	5	5	5	4	4	5	4	4	5	5	5	5	4	5
5	5	5	4	5	5	5	5	5	5	4	5	4	5	5	5	5	5	4	5
5	5	5	4	5	7	5	5	5	5	5	5	5	5	5	5	5	5	4	5
5	7	5	5	5	7	9	5	5	5	5	5	5	5	5	5	5	5	5	5
5	7	5	5	5	7	9	6	9	5	5	5	5	5	5	5	6	5	5	5
5	9	7	5	9	9	9	7	11	5	5	7	5	5	6	5	7	5	9	7
6	9	7	5	9	9	9	7	11	5	7	7	9	5	7	6	9	5	11	9
9	11	9	5	11	11	11	9	11	7	9	9	11	9	9	6	9	7	11	9
9	11	11	5	11	11	11	11	11	9	9	9	11	9	9	7	11	9	11	9
11	11	11	7	11	11	11	11	11	11	9	11	11	11	11	7	11	11	11	11
11	11	12	11	11	11	11	11	11	11	11	11	11	11	11	7	11	11	11	11
13	11	13	11	11	11	11	13	11	11	13	13	11	11	11	11	13	11	13	13
13	13	13	13	13	13	13	13	11	13	13	13	13	12	13	11	13	12	13	13

12	8	11	13	12	9	9	11	9	13	10	12	9	13	11	13	11	12	10	10
2	2	1	0	2	2	4	1	1	1	3	2	1	2	2	0	2	1	1	3
2	1	2	1	1	1	1	2	0	1	2	2	1	0	1	0	2	0	2	2

X	16	11	14	14	15	12	14	14	10	15	15	16	11	15	14	13	15	13	13	15

2	5	2	2	5	5	5	3	8	3	1	2	5	3	3	2	3	3	5	2
0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0

2	5	3	2	5	5	5	3	8	3	1	2	5	4	3	2	3	4	5	2

Y	18	16	17	16	20	17	19	17	18	18	16	18	16	19	17	15	18	17	18	17

50%

35 M1

20 M2

1	2	3	**4**	5
6	7	8	9	10
11	12	13	14	15

2	2	2	2	4	4	2	2	3	2	2	2	1	2	1	2	1	2	2	1
2	2	4	2	4	4	3	2	4	4	2	2	2	2	2	2	2	2	2	2
2	2	4	4	4	4	4	2	4	4	2	4	2	2	2	4	4	3	2	4
2	4	4	4	4	5	4	2	4	4	4	4	4	2	2	4	4	4	4	4
4	4	4	4	5	5	4	2	4	4	4	4	4	2	4	4	4	4	4	4
4	4	5	5	5	5	5	2	4	4	4	4	4	4	4	4	4	4	4	4
4	4	5	5	5	5	5	4	4	5	4	4	4	4	4	5	4	4	4	4
5	4	5	5	5	5	5	4	4	5	4	4	4	4	4	5	4	4	5	4
5	4	5	5	5	5	5	5	4	5	5	5	4	4	4	5	5	4	5	5
5	4	5	5	5	7	5	5	5	5	5	5	5	4	5	5	5	4	5	5
5	5	5	7	7	9	5	5	5	5	5	5	5	5	5	5	5	5	5	5
5	5	5	7	8	9	5	5	5	5	5	5	5	5	5	5	5	5	5	5
5	5	5	9	11	11	7	5	5	5	5	7	5	5	5	5	5	5	7	5
5	5	7	9	11	11	7	5	5	5	7	7	5	5	5	7	5	5	7	5
7	5	9	11	11	11	9	7	5	7	11	9	5	5	5	9	5	5	9	5
11	11	11	13	13	12	11	7	5	9	11	9	5	9	7	9	9	5	9	7
11	11	11	13	13	13	11	11	7	11	11	9	7	9	9	9	11	5	9	9
13	12	11	13	13	13	11	11	9	11	12	11	7	11	9	11	11	7	11	9
13	12	12	13	14	14	13	12	11	13	12	12	9	11	11	13	12	11	11	11
13	12	13	13	14	14	13	13	13	14	13	12	11	14	11	14	14	11	13	11

10	12	12	8	10	9	11	8	16	13	10	10	13	10	11	11	13	15	9	13
0	0	1	2	1	2	1	0	1	1	0	3	1	2	2	3	1	0	3	2
3	0	1	5	5	4	2	1	1	2	1	0	0	1	0	2	1	0	1	0

X	13	12	14	15	16	15	14	9	18	16	11	13	14	13	13	16	15	15	13	15

2	2	3	1	3	3	3	2	1	2	3	1	1	2	2	1	2	2	2	2
0	3	1	0	0	1	0	1	0	0	2	2	0	0	0	0	1	0	0	0

2	5	4	1	3	4	3	3	1	2	5	3	1	2	2	1	3	2	2	2

Y	15	17	18	16	19	19	17	12	19	18	16	16	15	15	15	17	18	17	15	17

55%	1	2	3	**4**	5
35 M1	6	7	8	9	10
20 M2	11	12	13	14	15

2	2	2	2	1	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
4	3	2	2	2	2	4	2	2	2	2	2	4	2	2	2	2	2	2	4
4	4	2	4	2	2	4	4	4	4	2	2	4	2	2	2	2	2	2	4
4	4	2	4	4	3	4	4	4	4	4	2	4	4	3	2	2	4	2	4
4	4	3	4	4	4	4	4	4	4	4	2	4	4	2	4	4	2	4	4

4	4	4	4	4	4	5	4	4	4	4	4	4	4	4	4	4	4	4	4
4	4	4	4	4	4	5	4	4	5	4	4	4	4	4	4	4	4	4	5
4	4	4	4	4	4	5	4	4	5	4	4	5	5	4	4	4	4	4	5
4	5	4	5	4	4	5	4	4	5	5	4	5	5	4	4	4	5	5	5
5	5	4	5	4	5	5	5	5	5	5	4	5	5	5	4	4	5	5	5
5	5	5	5	4	5	5	9	5	5	5	4	5	5	5	4	5	5	5	5
5	5	5	5	5	5	7	11	5	5	7	4	5	5	5	4	5	5	5	5
5	5	5	5	5	5	8	11	5	5	8	5	5	7	5	5	5	5	5	5
5	7	5	5	5	5	8	11	5	5	11	5	5	8	5	5	5	5	5	5
5	7	5	7	5	11	11	11	5	6	11	7	5	9	5	5	5	5	6	5
9	7	5	11	7	11	11	11	5	11	13	9	7	11	6	5	11	7	11	9
11	8	7	11	11	11	11	11	6	11	13	11	7	11	8	5	11	9	11	11
11	9	11	11	11	11	11	13	7	11	14	11	7	11	9	11	11	11	11	11
12	9	11	13	11	11	11	14	9	11	14	11	8	14	11	13	13	11	11	11
14	13	11	13	11	11	13	14	11	11	14	13	9	14	13	14	14	11	11	14

14	12	12	12	12	11	10	8	14	12	8	9	14	9	12	12	11	12	9	14
1	3	0	0	0	0	2	1	1	0	1	1	2	2	2	0	0	1	0	1
1	1	0	2	0	0	1	3	0	0	5	1	0	2	1	2	2	0	0	1

X	16	16	12	14	12	11	13	12	15	12	14	11	16	13	15	14	13	13	9	16

2	0	3	3	4	6	5	6	1	5	2	3	0	3	1	1	3	3	5	3
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

3	0	3	3	4	6	5	6	1	5	2	3	0	3	1	1	3	3	5	3

Y	19	16	15	17	16	17	18	18	16	17	16	14	16	16	16	15	16	16	14	19

60%

35 M1

20 M2

1	2	3	**4**	5
6	7	8	9	10
11	12	13	14	15

1	2	1	1	1	1	1	1	2	1	1	1	2	1	1	1	1	1	2	1
1	2	1	2	2	2	1	1	2	2	1	1	4	2	2	1	2	2	2	2
2	2	2	2	2	2	2	2	2	2	1	2	4	2	2	2	2	2	2	2
2	2	2	2	2	2	2	2	2	2	1	2	4	2	2	2	2	2	2	2
2	2	2	2	2	2	2	2	4	2	2	2	4	2	3	2	2	2	2	2
2	3	2	2	2	2	2	4	4	2	2	2	4	2	3	4	2	2	4	2
2	4	2	2	2	4	2	4	4	4	2	2	4	4	4	5	4	2	4	2
2	4	4	4	4	4	4	4	4	4	2	3	5	4	4	5	4	4	4	2
2	4	4	4	4	4	4	4	4	4	2	4	5	4	4	5	5	4	5	2
2	4	4	4	4	5	4	5	4	4	5	4	5	4	4	5	5	4	5	4
3	4	4	5	4	5	5	5	5	4	5	4	5	5	4	5	5	4	5	4
4	5	4	5	4	5	5	5	5	4	5	4	5	5	4	5	5	5	5	4
4	5	5	5	5	5	5	5	5	5	5	4	5	5	5	5	5	5	5	5

4	5	5	5	5	5	5	5	5	5	5	5	7	5	5	5	5	5	5	5
4	5	8	5	5	5	7	5	5	5	8	5	8	5	5	5	5	7	5	7
4	6	8	7	5	5	7	5	5	5	9	5	8	5	5	5	7	8	5	8
4	6	9	8	5	9	7	7	5	5	11	7	9	7	5	5	7	8	7	8
5	8	11	8	5	9	8	9	5	5	11	7	11	8	5	7	9	9	7	9
5	11	11	9	6	11	11	9	7	5	11	8	11	9	7	11	11	11	7	11
7	11	11	11	11	11	11	11	11	7	11	9	11	11	11	11	11	11	8	11

9	10	7	8	11	10	7	11	14	13	5	9	12	10	14	12	9	7	11	5
0	1	3	3	0	2	1	2	0	0	2	2	3	2	0	0	1	3	1	3
11	9	10	9	9	8	12	7	6	7	13	9	5	8	6	8	10	10	8	12

X	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20
	0	2	3	1	1	2	2	1	1	0	4	0	3	1	1	2	2	2	0	2
	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	0	2	3	1	1	2	2	1	1	0	4	0	3	1	1	2	2	2	0	2
Y	20	22	23	21	21	22	22	21	21	20	24	20	23	21	21	22	22	22	20	22

65%		1	2	3	**4**	5
35	M1	6	7	8	9	10
20	M2	11	12	13	14	15

2	2	2	2	2	2	2	2	1	1	1	1	2	1	2	2	2	1	1	1
2	2	2	2	2	2	2	2	2	2	1	2	3	2	2	2	2	2	2	2
2	2	2	2	2	2	2	2	2	2	2	2	4	2	2	2	2	2	2	2
2	2	4	2	2	2	2	2	2	2	2	2	4	2	2	2	2	2	2	2
4	4	4	2	2	2	4	4	2	2	2	4	4	4	4	3	4	2	2	2
4	4	5	2	2	4	4	4	4	2	2	4	4	4	4	4	4	2	2	2
4	4	5	3	4	4	4	4	4	2	2	5	4	4	4	4	4	2	2	2
4	5	5	4	4	4	4	4	4	4	2	5	4	4	4	4	4	2	3	2
5	5	5	4	4	4	4	5	4	4	2	5	5	4	5	4	4	2	4	2
5	5	5	4	4	4	4	5	4	4	4	5	5	5	5	4	5	4	4	4
5	5	5	4	4	5	5	5	5	4	4	5	5	5	5	5	5	4	4	4
5	5	5	5	4	5	5	5	5	5	5	5	5	5	5	5	5	4	4	4
5	5	5	5	4	8	5	7	5	5	5	5	5	5	5	5	5	5	5	5
7	5	5	5	5	8	7	8	5	5	5	5	5	5	5	5	5	5	5	5
7	7	5	5	5	9	7	8	5	5	5	8	5	7	8	6	7	5	5	5
8	7	7	5	5	9	8	9	5	5	5	8	8	8	11	6	7	5	5	5
9	8	8	7	5	9	11	9	7	7	5	9	11	9	11	7	9	5	5	9
9	11	8	8	5	9	11	11	8	8	8	9	11	11	11	8	11	7	9	9
9	11	8	9	5	11	11	11	8	8	8	9	11	11	11	11	11	9	11	9
11	11	11	11	11	11	11	11	8	9	9	11	11	11	13	11	15	9	11	11

9	10	12	10	13	7	9	8	11	9	8	10	14	10	10	10	10	8	10	7
4	1	3	2	0	6	1	4	3	3	3	5	1	2	1	1	1	2	1	3
0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0

X	13	11	15	12	13	13	10	12	14	12	11	15	15	12	12	11	12	10	11	10

1	3	1	1	1	2	4	3	0	0	0	1	4	3	4	2	2	0	2	1
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

	1	3	1	1	1	2	4	3	0	0	0	1	4	3	4	2	2	0	2	1
Y	14	14	16	13	14	15	14	15	14	12	11	16	19	15	16	13	14	10	13	11

70%	1	2	3	**4**	5
35 M1	6	7	8	9	10
20 M2	11	12	13	14	15

2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
4	2	2	2	2	2	2	2	2	2	2	2	2	2	3	2	2	2	2	2
4	2	2	2	2	4	2	3	3	2	2	3	2	2	3	2	2	2	2	2
4	2	2	4	3	4	2	4	4	2	3	4	3	2	4	2	2	2	2	4
4	4	4	4	3	4	3	4	4	3	4	4	4	3	4	3	2	4	2	4
4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	3	4	4	3	4
4	4	4	4	4	5	4	4	4	4	5	4	4	4	4	4	4	4	4	4
5	4	4	4	4	5	5	5	4	4	5	4	4	4	5	4	4	4	4	4
5	4	4	5	4	5	5	5	4	4	5	4	4	5	5	4	5	5	4	4
5	4	4	5	5	5	5	5	5	5	5	5	4	5	5	4	5	5	5	5
5	4	5	5	5	5	5	5	5	5	5	5	5	5	5	4	5	5	5	5
5	5	5	5	5	5	5	5	5	5	5	5	5	7	6	5	5	5	5	5
5	5	5	5	5	5	8	5	5	5	5	5	5	7	8	5	5	5	5	5
8	5	7	7	7	5	8	8	7	9	7	7	8	8	8	5	7	5	5	5
8	5	8	8	7	8	8	9	8	9	7	8	8	9	9	5	7	5	5	7
9	7	9	8	8	8	9	9	9	9	8	9	9	9	9	5	8	5	7	8
9	8	11	9	8	9	11	9	11	9	9	9	11	9	9	5	11	5	8	8
11	9	11	11	11	9	11	9	11	11	9	11	12	11	11	11	11	8	8	9
11	14	11	14	14	11	15	9	11	11	9	11	14	11	11	11	11	9	14	11

12	11	9	10	10	12	8	11	11	9	10	11	10	7	10	13	8	13	10	11
4	2	2	3	2	4	4	6	2	4	4	3	3	4	5	0	1	2	2	3
0	1	0	1	1	0	1	0	0	0	0	0	1	0	0	0	0	0	1	0

X	16	14	11	14	13	16	13	17	13	13	14	14	14	11	15	13	9	15	13	14

2	0	3	1	1	1	2	0	3	2	0	2	1	2	2	2	3	0	0	1
0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0

	2	0	3	1	1	1	2	0	3	2	0	2	2	2	2	2	3	0	0	1
Y	18	14	14	15	14	17	15	17	16	15	14	16	16	13	17	15	12	15	13	15

75%

	1	2	3	**4**	5
35 M1	6	7	8	9	10
20 M2	11	12	13	14	15

2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
3	2	2	2	2	2	2	2	2	3	2	2	2	2	3	4	2	2	2	2
4	2	2	4	2	2	2	2	3	4	2	2	3	2	4	4	2	2	3	2
4	2	2	4	2	2	4	2	3	4	2	4	4	2	4	4	2	2	4	2
4	2	4	4	2	4	4	2	4	4	2	4	4	2	4	4	2	4	4	3
4	2	4	4	2	4	4	2	4	4	4	4	4	2	4	5	4	4	4	3
4	3	4	4	2	4	4	4	4	4	4	4	4	2	4	5	4	4	4	3
5	4	4	4	4	4	4	4	4	5	4	5	4	4	4	5	4	4	4	4
5	4	4	4	4	5	4	4	4	5	4	5	4	4	4	5	5	5	4	4
5	4	5	4	4	5	4	4	4	5	4	5	4	4	5	5	5	5	4	4
5	4	5	5	4	5	5	5	4	5	4	5	5	4	5	7	5	5	4	4
5	4	5	5	5	5	5	5	4	5	5	5	5	4	5	8	5	5	5	5
5	4	7	5	5	5	5	6	4	5	5	5	5	5	5	8	7	5	5	5
5	4	7	5	5	7	5	7	5	5	5	7	5	5	5	8	9	6	5	5
5	4	8	8	7	8	8	8	5	5	8	8	5	5	5	9	9	7	5	5
8	5	8	8	8	8	9	8	5	7	8	8	5	9	5	9	9	8	5	7
9	5	9	9	9	9	9	8	5	7	8	9	5	9	5	11	9	8	5	8
11	6	9	10	11	9	11	9	9	9	9	11	8	10	7	11	11	11	9	8
11	15	11	10	15	9	11	9	11	9	9	15	8	11	7	11	15	11	10	9

14	11	8	12	7	9	11	6	15	14	9	10	15	8	16	9	7	9	15	11
2	0	4	5	2	5	3	5	1	2	5	3	2	3	0	5	4	2	2	3
0	1	0	0	1	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0

X	16	12	12	17	10	14	14	11	16	16	14	14	17	11	16	14	12	11	17	14

2	0	1	0	1	0	2	0	1	0	0	1	0	1	0	3	1	2	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

	2	0	1	0	1	0	2	0	1	0	0	1	0	1	0	3	1	2	0	0
Y	18	12	13	17	11	14	16	11	17	16	14	15	17	12	16	17	13	13	17	14

80%

1	2	3	**4**	5

35 M1	6	7	8	9	10
20 M2	11	12	13	14	15

2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
2	2	2	2	2	2	2	2	2	2	2	2	2	3	2	2	2	2	2	2
3	2	2	2	2	2	2	2	2	2	2	2	2	3	2	2	2	2	2	2
4	2	4	2	4	3	2	4	2	4	4	2	2	3	2	2	2	2	2	2
4	2	4	3	4	3	2	4	2	4	4	2	2	4	3	2	2	2	2	2
5	2	4	4	4	3	2	4	3	4	4	4	2	4	3	2	3	2	2	4
5	2	4	4	4	4	2	4	3	4	4	4	2	4	3	2	4	2	4	4
5	2	4	4	4	4	2	4	3	4	4	4	2	5	4	2	4	4	4	4
5	2	4	4	4	4	4	4	3	5	4	4	4	5	4	2	4	4	4	4
5	3	4	4	4	4	4	4	4	5	4	4	4	5	4	2	5	4	4	4
5	4	4	4	5	4	4	5	4	5	4	4	4	5	4	3	5	5	4	4
7	4	5	4	5	5	4	5	4	5	5	5	4	5	4	3	5	5	4	5
8	5	5	5	5	5	4	5	4	7	7	5	5	7	4	4	6	7	4	5
8	5	7	5	5	5	4	5	5	7	8	5	5	7	5	4	7	8	5	8
8	7	8	5	5	5	4	7	7	8	8	5	5	8	5	5	9	9	5	8
9	9	8	5	5	8	5	7	8	8	9	7	7	8	5	5	9	10	5	9
9	10	8	5	5	8	5	7	8	8	9	8	8	9	7	5	10	10	7	10
9	10	9	8	5	9	7	7	9	10	10	8	9	9	8	5	10	10	15	10
10	10	10	8	8	10	8	7	11	15	10	10	10	10	10	5	11	15	15	15
15	15	10	9	10	15	9	15	11	15	15	10	10	10	15	7	11	15	15	15

9	5	10	13	15	12	9	11	9	9	9	10	7	11	12	9	7	5	10	8
7	4	6	3	2	4	2	0	3	4	6	4	4	6	2	0	4	5	0	5
1	1	0	0	0	1	0	1	0	2	1	0	0	0	1	0	0	2	3	2

X	17	10	16	16	17	17	11	12	12	15	16	14	11	17	15	9	11	12	13	15

0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	2	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	2	0	0	0

Y	17	10	16	16	17	17	11	12	14	15	16	14	11	17	15	9	13	12	13	15

85%	1	2	3	**4**	5
35 M1	6	7	8	9	10
20 M2	11	12	13	14	15

2	2	2	2	2	2	2	2	2	2	2	2	2	2	1	2	2	2	2	2
2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
4	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
4	2	3	2	2	2	2	2	4	2	2	2	3	2	2	2	2	2	2	2

4	3	4	2	2	2	2	2	4	4	3	2	4	2	4	2	2	4	2	2
4	4	4	2	2	4	2	4	4	4	4	2	4	2	4	2	2	4	2	3
4	4	5	4	2	4	2	4	4	5	4	2	4	2	4	4	2	4	2	4
4	5	5	4	2	4	3	5	5	5	4	3	5	2	4	4	2	5	4	5
4	5	5	4	4	4	5	5	5	5	4	4	5	4	4	5	2	5	4	5
5	5	5	4	4	4	5	5	5	5	4	4	5	4	5	5	3	5	4	5
5	7	5	5	4	5	5	5	5	5	5	4	5	4	5	7	4	5	4	5
5	8	5	5	4	5	5	5	5	5	5	4	5	4	5	7	4	5	5	5
5	8	5	5	5	5	5	5	5	8	7	5	5	4	5	8	4	7	5	5
5	10	5	5	5	5	5	7	5	10	7	5	7	5	5	8	4	7	5	5
7	10	7	5	5	5	8	8	5	10	8	5	7	5	8	8	4	8	5	5
8	10	7	5	5	5	8	8	5	10	8	7	8	5	8	8	4	8	5	5
8	11	7	5	7	7	8	10	7	10	10	7	8	7	8	8	5	10	8	8
8	15	8	5	8	7	8	10	7	10	10	7	9	7	9	10	5	10	10	8
8	15	8	9	8	8	10	10	8	10	11	8	10	7	9	10	10	10	11	15
10	15	10	11	10	8	10	10	8	15	15	10	10	7	15	15	10	11	15	15

12	6	11	12	8	11	7	8	13	8	8	8	10	8	10	4	9	8	9	11
5	5	3	1	3	2	6	6	2	7	4	2	5	0	5	7	2	5	2	2
0	3	0	0	0	0	0	0	0	1	1	0	0	0	1	1	0	0	1	2

X	17	14	14	13	11	13	13	14	15	16	13	10	15	8	16	12	11	13	12	15

0	1	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	1	1	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

0	1	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	1	1	0

Y	17	15	14	14	11	13	13	14	15	16	14	10	15	8	16	12	11	14	13	15

90%

35 M1

20 M2

1	2	3	**4**	5
6	7	8	9	10
11	12	13	14	15

	2	2	5	8
0	0	2	0	1
0	0	0	0	0

2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	1	2	2	2	2
2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
2	2	2	2	2	2	2	2	2	3	2	2	2	2	2	2	2	2	2	2
2	2	2	2	2	2	2	2	2	3	2	2	2	2	2	2	3	4	4	4
2	4	2	2	2	3	2	2	2	4	4	2	2	2	3	4	3	4	4	4
2	5	2	3	2	4	2	2	3	4	5	3	2	2	4	4	4	4	4	4
2	5	4	4	2	4	3	2	4	4	5	4	2	4	4	4	4	4	4	4
2	5	4	4	4	4	4	2	4	4	5	4	3	4	4	4	4	4	5	4
3	5	5	4	4	4	4	2	4	4	5	4	4	4	4	4	4	5	5	4
4	5	5	4	4	5	4	4	4	5	5	4	4	5	4	4	4	5	5	4
4	5	5	5	4	5	4	4	5	5	5	5	4	5	4	5	4	5	5	5

4	5	5	5	4	5	4	4	5	5	5	5	4	5	5	5	5	5	7	5
4	5	5	5	4	5	5	4	5	5	5	7	5	5	5	5	5	7	7	5
4	5	7	5	5	5	5	5	5	5	5	7	5	5	5	5	7	8	7	5
5	5	7	5	5	7	7	5	5	5	5	7	7	5	7	5	7	8	7	5
5	7	8	5	5	7	9	5	5	5	5	8	7	5	7	5	8	8	8	5
5	8	8	7	5	8	10	7	7	5	7	8	8	7	8	7	8	10	8	7
7	8	8	7	7	8	10	8	8	8	7	8	8	8	8	8	8	10	9	8
9	9	10	7	7	8	10	8	8	8	7	8	10	10	8	8	10	10	10	8
10	10	10	8	9	10	10	9	10	10	8	9	10	10	9	8	10	10	11	8

9	11	7	11	10	10	8	7	11	15	12	7	7	10	10	12	10	9	8	13
2	4	5	1	1	4	5	3	3	3	1	5	4	3	4	3	5	7	4	3
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

X	11	15	12	12	11	14	13	10	14	18	13	12	11	13	14	15	15	16	12	16

0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0

Y	11	15	12	12	11	14	13	10	14	18	13	12	11	13	14	15	15	16	13	16

A.2.1.6 CS1 Additional ProMps Results

10%

		1	2	3	4	5
35	M1	6	7	8	9	10
20	M2	11	12	13	14	15

Cell 15 Prediction

4	4	3	3	5	3	4	9	5	8	9	5	3	4	5	3	3	3	3	3
5	4	5	3	5	5	5	10	9	10	9	5	5	4	5	3	10	5	9	4
5	5	5	5	9	9	5	10	10	10	10	5	5	5	5	5	10	9	10	10
9	9	9	5	10	10	9	10	10	10	10	9	9	5	5	10	10	9	10	10
9	9	10	5	10	10	10	10	10	10	10	9	9	9	5	10	10	9	10	10
10	10	10	10	10	10	10	10	10	10	10	10	10	9	9	12	10	10	10	10
10	10	10	10	10	10	10	12	12	10	10	10	10	9	9	12	10	10	10	12
10	10	10	10	10	10	10	12	12	12	10	10	10	10	10	12	10	10	12	12
10	10	10	10	12	10	12	12	12	12	10	10	12	10	10	12	11	10	12	12
11	12	12	10	12	10	12	12	12	12	12	10	12	10	12	12	11	10	12	12
11	12	12	10	12	10	15	14	12	12	12	12	15	10	12	15	12	11	12	12
12	12	15	12	12	10	15	15	12	12	12	12	15	11	12	15	12	11	12	12
12	12	15	12	12	12	15	15	12	15	12	15	15	12	12	15	12	12	12	15
12	12	15	12	12	15	15	15	15	15	15	15	15	12	15	15	12	12	12	15
15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	12	15	15
15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	12	15	15
15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	12	15	15
15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	12	15	15
15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15

3	3	3	5	2	2	3	0	1	0	0	3	3	4	5	3	1	2	1	2
6	6	6	6	6	10	5	6	5	7	9	7	5	7	4	2	7	8	6	4
6	6	9	6	6	7	10	10	7	8	7	8	10	6	7	10	6	2	6	8

X	15	15	18	17	14	19	18	16	13	15	16	18	18	17	16	15	14	12	13	14

2	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	2	2	0	0
3	5	2	3	6	1	2	4	7	5	4	2	2	2	4	5	4	6	7	6

	5	5	2	3	6	1	2	4	7	5	4	2	2	3	4	5	6	8	7	6
Y	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20

15%

		1	2	3	4	5
35	M1	6	7	8	9	10
20	M2	11	12	13	14	15

5	4	3	10	9	3	3	3	5	5	3	5	3	3	3	5	5	3	5	4
5	9	3	10	10	4	5	4	9	5	5	5	5	5	3	5	9	9	5	9
9	9	3	10	10	4	9	5	9	5	10	9	5	10	3	9	10	9	10	9
10	9	5	11	10	5	9	5	9	10	10	10	9	10	4	10	10	10	10	10
10	9	5	12	10	5	10	10	10	10	10	10	9	10	5	10	11	10	10	10
10	10	9	12	10	10	10	10	10	10	10	10	9	10	5	10	11	10	10	10
10	10	9	12	10	10	10	10	11	10	10	10	10	11	10	10	12	10	10	10
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4	6	5	10	7	6	9	8	8	7	6	10	8	6	7	8	7	7	6	9

X	14	14	15	13	14	14	16	16	14	16	17	17	16	12	14	15	11	14	14	16

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Y	6	6	5	7	6	6	4	4	6	4	3	3	4	8	6	5	9	6	6	4

20%

	1	2	3	4	5
35 M1	6	7	8	9	10
20 M2	11	12	13	14	15

3	3	4	5	5	3	4	5	3	3	3	5	5	4	5	5	3	3	3	4
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X	17	18	15	19	14	17	12	16	15	17	14	18	16	15	16	16	12	12	17	14
	0	1	0	0	1	1	1	0	0	1	1	0	0	0	0	0	0	1	0	0
	3	1	5	1	5	2	7	4	5	2	5	2	4	5	4	4	8	7	3	6
Y	3	2	5	1	6	3	8	4	5	3	6	2	4	5	4	4	8	8	3	6

25%

	1	2	3	4	5
35 M1	6	7	8	9	10
20 M2	11	12	13	14	15

5	3	3	9	3	10	5	3	3	4	5	9	5	3	3	4	3	3	3	4
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11	10	10	10	10	12	10	10	10	9	10	12	10	10	10	10	5	9	10	10
12	10	12	10	10	12	10	10	10	10	10	12	10	10	12	10	10	10	10	10
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	11	4	7	5	5	9	6	6	7	7	7	11	4	4	7	10	5	5	4	6
X	16	11	13	12	15	13	15	13	16	18	14	13	11	12	13	18	14	15	17	14
	1	1	0	0	1	0	0	1	1	0	0	1	0	0	0	0	0	0	0	0
	3	8	7	8	4	7	5	6	3	2	6	6	9	8	7	2	6	5	3	6

	4	9	7	8	5	7	5	7	4	2	6	7	9	8	7	2	6	5	3	6
Y	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20

30%

	1	2	3	4	5
35 M1	6	7	8	9	10
20 M2	11	12	13	14	15

3	3	3	3	4	5	4	5	4	3	4	4	3	9	4	3	4	3	3	3
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3	5	5	4	9	8	10	9	10	10	10	9	10	10	5	5	9	5	4	5
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10	12	10	9	10	10	10	10	12	10	12	10	10	10	12	10	10	10	9	10
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12	15	12	10	11	10	12	12	12	12	15	10	12	12	12	10	12	10	10	12
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	7	3	6	7	9	10	7	7	2	6	4	9	5	7	1	7	7	7	7	6
	4	12	5	6	5	4	7	8	9	5	12	6	4	5	8	7	6	2	4	6
X	14	18	15	18	15	16	16	17	13	13	18	17	11	12	13	18	15	14	17	15
	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
	6	2	5	2	4	4	4	3	7	7	2	3	9	7	7	2	5	6	3	5
	6	2	5	2	5	4	4	3	7	7	2	3	9	8	7	2	5	6	3	5
Y	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20

35%

	1	2	3	4	5
35 M1	6	7	8	9	10
20 M2	11	12	13	14	15

5	5	10	5	5	3	3	5	3	3	10	3	3	4	4	3	5	5	3	3
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9	9	10	9	9	5	5	5	5	5	10	5	9	10	9	3	9	9	5	8
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12	10	10	10	10	10	12	10	10	10	10	10	12	10	10	10	10	10	10	9
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	1	2	0	1	2	3	4	3	3	3	0	5	2	1	2	3	2	2	5	2
	5	9	8	8	8	4	2	4	5	6	7	5	4	6	8	4	5	7	4	9
	10	4	10	6	5	3	9	7	6	5	6	8	8	7	4	6	7	6	3	3
X	16	15	18	15	15	10	15	14	14	14	13	18	14	14	14	13	14	15	12	14
	0	1	0	0	2	0	0	0	0	0	0	0	0	1	0	0	2	0	0	0

	4	4	2	5	3	10	5	6	6	6	7	2	6	5	6	7	4	5	8	6
	4	5	2	5	5	10	5	6	6	6	7	2	6	6	6	7	6	5	8	6
Y	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20

40%

	1	2	3	4	5
35 M1	6	7	8	9	10
20 M2	11	12	13	14	15

5	3	4	3	10	3	5	3	5	3	3	3	4	4	3	9	3	4	5	5
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9	10	9	10	10	5	10	9	10	5	9	10	5	10	5	10	5	10	10	10
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10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	9	10	10	10
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10	12	12	10	10	10	10	10	12	10	10	10	10	10	10	10	9	12	10	10
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12	12	12	10	10	12	10	10	12	10	10	11	10	12	10	12	10	12	10	11
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15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15

	1	2	2	2	0	3	1	2	1	3	2	2	3	1	3	0	3	2	1	1
	6	3	3	8	10	5	8	8	5	6	10	6	7	6	6	7	7	3	8	6
	8	11	9	2	7	8	5	2	9	7	6	6	4	10	3	7	6	9	8	6
X	15	16	14	12	17	16	14	12	15	16	18	14	14	17	12	14	16	14	17	13

	0	0	0	2	0	0	2	1	0	1	1	2	0	0	0	1	0	1	0	3
	5	4	6	6	3	4	4	7	5	3	1	4	6	3	8	5	4	5	3	4
	5	4	6	8	3	4	6	8	5	4	2	6	6	3	8	6	4	6	3	7
Y	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20

45%

	1	2	3	4	5
35 M1	6	7	8	9	10
20 M2	11	12	13	14	15

3	5	3	3	3	4	5	4	5	3	4	3	3	4	3	5	3	3	4	5
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4	9	5	4	10	9	9	5	10	5	5	9	5	10	9	9	5	3	9	10
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10	10	12	9	12	10	10	9	10	10	10	10	10	10	10	10	10	10	10	11
10	10	12	10	12	10	10	10	10	12	10	10	10	10	10	10	10	10	10	12
10	11	12	10	15	10	10	10	12	12	10	10	10	10	10	10	10	12	10	12
11	12	12	10	15	10	12	10	12	12	10	10	12	10	12	12	10	12	12	12
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15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15

	4	2	3	5	1	2	1	5	1	3	3	2	5	1	2	2	4	3	2	1
	5	6	2	7	3	8	8	8	7	4	7	8	4	10	7	7	6	5	7	4
	6	6	8	6	12	8	5	5	6	7	6	8	9	6	6	7	7	7	7	9
X	15	14	13	18	16	18	14	18	14	14	16	18	18	17	15	16	17	15	16	14

	2	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2
	3	5	7	2	3	2	6	2	6	6	4	2	2	3	5	4	3	5	4	4
	5	6	7	2	4	2	6	2	6	6	4	2	2	3	5	4	3	5	4	6
Y	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20

50%

	1	2	3	4	5
35 M1	6	7	8	9	10
20 M2	11	12	13	14	15

9	3	4	5	5	10	4	5	4	3	4	5	3	3	3	9	3	3	4	4
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	13	4	2	5	6	6	6	8	4	4	4	8	7	5	7	8	5	6	6	7
Y	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20

55%

	1	2	3	4	5
35 M1	6	7	8	9	10
20 M2	11	12	13	14	15

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X	15	15	19	16	12	15	14	14	15	13	15	18	13	14	16	15	16	15	14	15
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	5	5	1	4	8	5	6	6	5	7	5	2	7	6	4	5	4	5	6	5
Y	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20

60%

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35 M1	6	7	8	9	10
20 M2	11	12	13	14	15

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X	15	17	14	15	16	17	19	14	17	15	16	16	15	11	15	14	15	16	15	15
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	5	3	6	5	4	3	1	6	3	5	4	4	5	9	5	6	5	4	5	5
Y	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20

65%

	1	2	3	4	5
35 M1	6	7	8	9	10
20 M2	11	12	13	14	15

3	5	5	5	5	9	5	3	3	4	5	5	5	5	3	3	3	3	3	3
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X	15	15	13	17	17	15	14	17	17	18	17	16	11	14	13	13	11	14	16	19
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	5	5	7	3	3	5	6	3	3	2	3	4	9	6	7	7	9	6	4	1
Y	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20

70%

	1	2	3	4	5
35 M1	6	7	8	9	10
20 M2	11	12	13	14	15

3	5	10	4	3	5	5	5	5	10	5	5	4	5	10	5	5	5	3	3
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	4	6	5	4	7	5	11	10	6	5	8	5	7	4	6	7	2	9	6	5
Y	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20

70%

	1	2
30 M1	6	7
20 M2	11	12

	3	3
	5	5
	5	10
	10	10
	10	10
	10	10
	10	10
	12	12
	12	12
	12	12
	12	12
	12	12
	12	12
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	15	15
	15	15
	15	15
	15	15
	15	15
	3	2
	4	5
	7	6
	14	13
	0	0
	6	7
0	6	7
0	20	20

75%

	1	2	3	4	5
35 M1	6	7	8	9	10
20 M2	11	12	13	14	15

10	4	9	4	5	10	10	4	4	4	5	4	10	4	4	4	5	5	5	4
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X	13	14	14	13	12	16	13	16	13	15	14	15	16	15	15	16	16	17	13	15
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	7	6	6	7	8	4	7	4	7	5	6	5	4	5	5	4	4	3	7	5
Y	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20

80%

	1	2	3	4	5
35 M1	6	7	8	9	10
20 M2	11	12	13	14	15

5	4	5	3	5	10	10	10	4	10	4	4	10	5	5	8	5	4	5	5
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	1	1	1	4	1	0	0	0	4	0	1	2	0	2	2	0	1	4	1	2
	5	4	3	3	2	6	6	2	2	5	3	4	1	7	6	3	3	4	2	6
	7	11	9	9	8	12	7	11	9	11	5	10	12	7	8	12	7	11	11	5
X	13	16	13	16	11	18	13	13	15	16	9	16	13	16	16	15	11	19	14	13
	2	0	1	0	1	0	0	1	0	0	2	0	0	1	0	0	1	0	0	0
	5	4	6	4	8	2	7	6	5	4	9	4	7	3	4	5	8	1	6	7
	7	4	7	4	9	2	7	7	5	4	11	4	7	4	4	5	9	1	6	7
Y	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20

85%

	1	2	3	4	5
35 M1	6	7	8	9	10
20 M2	11	12	13	14	15

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10	11	10	10	10	10	10	10	12	10	10	10	10	10	10	10	10	10	10	10
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X	16	8	17	10	15	14	14	15	15	14	18	15	17	14	17	14	15	13	16	14
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	4	12	3	10	5	6	6	5	5	6	2	5	3	6	3	6	5	7	4	6
Y	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20

90%		1	2	3	4	5
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20	M2	11	12	13	14	15

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X	15	12	12	17	15	15	14	15	14	14	13	15	15	14	11	18	15	15	15	15
	3	0	0	2	0	0	2	1	0	1	1	0	3	1	3	0	0	0	1	0
	2	8	8	1	5	5	4	4	6	5	6	5	2	5	6	2	5	5	4	5
	5	8	8	3	5	5	6	5	6	6	7	5	5	6	9	2	5	5	5	5
Y	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20

APPENDIX B

APPENDIX B

B.1 CS2: Human Movement in a Physically Assistive Dressing Task

B.1.1 Data Collection Further Analysis and Figures

B.2 Ethical Approval and Additional Sheets/Forms

B.2.1 CS2 Original Ethics Approval

University of the West of England
BRISTOL

University Research Ethics Committee

APPLICATION FOR ETHICAL REVIEW OF RESEARCH INVOLVING HUMAN PARTICIPANTS

Guidance Notes

These notes are intended to be read when completing the application form for ethical review of research involving human participants. The University's policy and procedures on research ethics may be found at http://www1.uwe.ac.uk/research/researchethics/. Please address any enquiries which are not covered in these notes to the contact (named below) for the Faculty Research Ethics Committee to which you are submitting your application.

This form may also be completed by researchers outside UWE who plan to conduct research within the University. (Note: Where a researcher has already obtained REC approval from another institution it may not be necessary to submit another application but you will need to send details of the research and evidence of approval to the REC chair before access may be granted to UWE staff and students.)

Research Ethics Committee contacts:

	Name	Email	Telephone
University Research Ethics Committee (UREC)	Alison Vaughton (Officer)	res.admin@uwe.ac.uk	0117 32 82872
Note: UREC reviews applications for ESRC-funded research, research involving surveying on a University-wide basis, and research conducted by staff in the Central Services. All other applications should be directed to the appropriate Faculty committee.			
Faculty Research Ethics Committees			
ACE	Lesley Brock (Officer)	lesley.brock@uwe.ac.uk	0117 32 84222
FBL	FBL REC Officer	bbs.researchethics@uwe.ac.uk	0117 32 86890
FET	Tom Brossard (Officer)	tom.brossard@uwe.ac.uk	0117 32 84250
HLS	Leigh Taylor (Officer)	leigh.taylor@uwe.ac.uk	0117 32 81170

External ethics approval

Where the work has already been subjected to ethical scrutiny, for example, by an NHS Research Ethics Committee through the National Research Ethics Service (NRES), you should indicate this on the form.

If your research involves NHS patients (including tissue or organs), or NHS data, you will usually need to get NHS REC approval. The UWE procedures recognise the burden placed on the researcher in applying for NHS REC approval. In order to assist PIs in this as far as possible, you are recommended to apply for NHS REC ethics approval first (using the IRAS form) and submit the letter of approval to your FREC or to UREC (as applicable). Where UWE is the sponsor for the study your FREC Chair will need to see the application before it can be authorised by the sponsor representative. This approach has been designed to retain the right of ultimate 'sign off' by the University without having to go through a separate protracted University process. It is important that PIs conducting research in the NHS appreciate that both UWE and NHS Ethics clearance will be needed and are separate. (Achievement of the one does not guarantee success with the other).

If you have already received ethical approval from an external Research Ethics Committee, you should provide evidence of this to UREC/FREC.

<u>Student applications</u>

For student applications, supervisors should ensure that all of the following are satisfied before the study begins:

- The topic merits further research;
- The student has the skills to carry out the research;
- The participant information sheet or leaflet is appropriate;
- The procedures for recruitment of research participants and obtaining informed consent are appropriate.

<u>Declaration</u>

This should be completed once all the following questions have been answered. Where the application is from a student, **a counter-signature from the supervisor is also necessary**. Applications without a supervisor signature will not be processed.

<u>Question 1</u>: Details of the proposed research – aims and objectives of the research

This should provide the reviewer of the application with sufficient detail to allow him/her to understand the nature of the project and its rationale, in terms which are clear to a lay reader. Do not assume that the reader knows you or your area of work. It may be appropriate to provide a copy of your research proposal.

<u>Question 2</u>: Details of the proposed research – Research methodology to be used

You should explain how you plan to undertake your research. A copy of the interview schedule/ questionnaire/observation schedule/focus group topic guide should be attached where applicable.

<u>Question 3</u>: Participant details – Participants from vulnerable groups

You must indicate if any of the participants in your sample group are in the categories listed. Any Department of Health funded research involving participants who might not have the capacity to consent may need to go through the new Social Care Research Ethics Committee (http://www.screc.org.uk/), unless it is already being reviewed through NRES. If your research subjects fall into any of the specified groups, you will need to justify their inclusion in the study, and find out whether you will require a Disclosure and Barring Service (DBS) (formerly Criminal Records Bureau -CRB) check.

Members of staff requiring DBS checks should contact Human Resources hr@uwe.ac.uk. DBS checks for students will usually be organised through the student's faculty, but students in faculties without a DBS countersignatory should contact Leigh Taylor (Leigh.Taylor@uwe.ac.uk).

Please note: Evidence of a DBS check should take the form of an email from the relevant countersignatory confirming the researcher has a valid DBS check for working with children and/or vulnerable adults. It will be the responsibility of the applicant to provide this confirmation.

Question 4: Participant details – Determination of sample size, identification and recruitment of participants

In this section, you should explain the rationale for your sample size and describe how you will identify and approach potential participants and recruit them to your study.

Question 5: Informed consent and withdrawal

Informed consent is an ethical requirement of the research process. Applicants should demonstrate that they are conversant with and have given due consideration to the need for informed consent and that any consent forms prepared for the study ensure that potential research participants are given sufficient information about a study, in a format they understand, to enable them to exercise their right to make an informed decision whether or not to participate in a research study.

Consent must be freely given with sufficient detail to indicate what participating in the study will involve. Withdrawal from future participation in research is always at the discretion of the participant. There should be no penalty for withdrawing and the participant is not required to provide any reason.

You should describe how you will obtain informed consent from the participants and, where this is written consent, include copies of participant information sheets and consent forms. Where other forms of consent are obtained (eg verbal, recorded) you should explain the processes you intend to use. See also data access, storage and security below.

Question 6: Confidentiality/anonymity

You should explain what measures you plan to take to ensure that the information provided by research participants is anonymised/pseudonymised (where appropriate) and how it will be kept confidential. In the event that the data are not to be anonymised/pseudonymised, please provide a justification.

Personal data is defined as ‘personal information about a living person which is being, or which will be processed as part of a relevant filing system. This personal information includes for example, opinions, photographs and voice recordings' (UWE Data Protection Act 1998, Guidance for Employees).

Question 7: Data access, storage and security

Describe how you will store the data, who will have access to it, and what happens to it at the end of the project. If your research is externally funded, the research sponsors may have specific requirements for retention of records. You should consult the terms and conditions of grant awards for details.

It may be appropriate for the research data to be offered to a data archive. If this is the case, it is important that consent for this is included in the participant consent form.

UWE IT Services provides data protection and encryption facilities - see http://www.uwe.ac.uk/its-staff/corporate/ourpolicies/intranet/encryption_facilities_provided_by_uwe_itservices.shtml

Question 8: Risk and risk management – Risks faced by participants

Describe ethical issues related to the physical, psychological and emotional wellbeing of the participants, and what you will do to protect their wellbeing. If you do not envisage there being any risks to the participants, please make it clear that you have considered the possibility and justify your approach.

Question 9: Risk and risk management – Potential risks to researchers

Describe any health and safety issues including risks and dangers for both the participants and yourself (if appropriate) and what you will do about them. This might include, for instance, arrangements to ensure that a supervisor or co-researcher has details of your whereabouts and a means of contacting you when you conduct interviews away from your base; or ensuring that a 'chaperone' is available if necessary for one-to-one interviews.

Question 10: Publication and dissemination of research results

Please indicate in which forms and formats the results of the research will be communicated.

Question 11: Other ethical issues

This gives the researcher the opportunity to raise any other ethical issues considered in planning the research or which the researcher feels need raising with the Committee.

APPLICATION FOR ETHICAL REVIEW

This application form should be completed by members of staff and Phd/ Prof Doc students undertaking **research which involves human participants**. U/G and M level students are required to complete this application form where their project has been referred for review by a supervisor to a Faculty Research Ethics Committee (FREC) in accordance with the policy at http://www1.uwe.ac.uk/research/researchethics/. For **research using human tissues**, please see separate policy, procedures and guidance linked from http://www1.uwe.ac.uk/research/researchethics/.

Please note that the research should not commence until written approval has been received from the University Research Ethics Committee (UREC) or Faculty Research Ethics Committee (FREC). You should bear this in mind when setting a start date for the project.

This form should be submitted electronically to the Officer of the Research Ethics Committee (see list above at page 1) together with all supporting documentation (research proposal, participant information sheet, consent form etc).

Please provide all the information requested and justify where appropriate.

For further guidance, please see http://www1.uwe.ac.uk/research/researchethics/ **(*applicants' information) or contact the officer for UREC/your Faculty Research Ethics Committee (details at page 1).***

Project Details:

Project title	Assistive interactive robotic system for support in dressing (I-DRESS)			
Is this project externally funded?			Yes	
If externally funded, please give details of project funder	**EU CHIST-ERA I-DRESS project /EPSRC EP/N021703/1**			
Proposed project start date	01/12/2015	Anticipated project end date	30/11/2018	

Applicant Details:

Name of researcher (applicant)	Dr Greg Chance
Faculty and Department	FET, Dept. Engineering Design and Mathematics
Status (Staff/ PG Student/MSc Student/Undergraduate)	Staff of Bristol Robotics Laboratory (BRL)
Email address	greg.chance@uwe.ac.uk
Contact postal address	Bristol Robotics Lab, T Block University of the West of England Frenchay Campus Bristol BS16 1QY
Contact telephone number	07968968985
Name of co-researchers (where applicable)	Dr Sanja Dogramadzi (0117 32 81301), Dr Praminda Caleb-Solly

(for completion by UWE REC) *Date received:* *UWE REC reference number:*

For All Applicants:		
Has external ethics approval been sought for this research?		No
If yes, please supply details:		

For student applicants only:	
Name of Supervisor / Director of Studies (for PG/MSc and UG student applicants)[1]	
Details of course/degree for which research is being undertaken	

[1]For student applications, supervisors should ensure that all of the following are satisfied before the study begins:

- The topic merits further research;
- The student has the skills to carry out the research;
- The participant information sheet or leaflet is appropriate;
- The procedures for recruitment of research participants and obtaining informed consent are appropriate.

Department of Supervisor / Director of Studies	
Supervisor's / Director of Studies' email address	
Supervisor's / Director of Studies' telephone number	
Supervisor's / Director of Studies' comments:	

Details of the proposed work:

PLEASE COMPLETE ALL SECTIONS. IF YOU THINK THE QUESTION IS NOT APPROPRIATE, PLEASE STATE WHY.

1. Aims, objectives of and background to the research: This research is being carried out as part of the EPSRC funded I-Dress project. This first phase of the research aims to determine what verbal and non-verbal commands (gestures, eye-gaze, body postures (adjustments and nudges) are used between two people when one person is supporting another person in a dressing support task. The objective is to find a statistically significant profile elicited from analysing a number of real dressing assistance scenarios and use these to determine interactions that are most effective. This data will then be used to build an interaction profile for a Human-Robot Interface.
2. Research methodology to be used (include a copy of the interview schedule/ questionnaire/ observation schedule where appropriate): We are interested in gathering data for two dressing support tasks. The dressing support tasks will be (a) putting on a coat over existing clothing and (b) putting on shoes. Participants will collaborate in pairs. For each dressing support task, the experiments will be performed in two phases: Phase I: Capturing natural verbal and non-verbal interaction between two people as one person supports another in the dressing support task. Phase II: Capturing verbal commands only. For this experiment one of the pair will 'act' as the robot (*robot-participant*) to help the other participant (the *dressing-participant*) put on the coat or shoes. The *dressing-participant* will give verbal commands only to the *robot-participant* to complete the dressing support task. The *robot-participant* will be requested to keep their eyes closed while following the verbal commands. Two facilitators will closely monitor the interaction and will provide a protocol for confirming the robot-participant's movement to ensure the movement is carried out safely, halting the task immediately if there is any risk to either participant is observed. During the experiments participants will be recorded on video to capture the verbal and non-verbal commands used. We will also be using a Vicon motion capture system to record the position of body joints: elbow, wrist, etc. using reflective markers to understand the movement of the *dressing-participant* during the task, i.e. do they assist the *robot-participant* by moving in a way that promotes successful dressing, as well as the robot-participant, to record their response to the commands and the dressing-participant's movements. Video footage will be privy to the researchers only. Once the task is complete the dressing vocabulary will be reported to the project team but will not contain personal information. Video footage will then be encrypted and stored on a secure server for the duration of the project.

The body position data from the Vicon system records only the position of the body joints. This information will be identified by a user reference, e.g. user 01, but will not include any personal information.

3. Selection of participants:

Will the participants be from any of the following groups?*(Tick as appropriate)*

☐ Children under 18

☐ Adults who are unable to consent for themselves[2]

☐ Adults who are unconscious, very severely ill or have a terminal illness

☐ Adults in emergency situations

☐ Adults with mental illness (particularly if detained under Mental Health Legislation)

☐ Prisoners

☐ Young Offenders

☐ Healthy Volunteers (where procedures may be adverse or invasive)

☐ Those who could be considered to have a particularly dependent relationship with the investigator, e.g. those in care homes, medical students

☐ Other vulnerable groups

☒ None of the above

([2] Please note, the Mental Capacity Act requires all intrusive research involving adults who are unable to consent for themselves to be scrutinised by an NHS Local Research Ethics Committee – Please consult the Chair of your Faculty Research Ethics Committee, or Alison Vaughton (RBI) for advice)

If any of the above applies, please justify their inclusion in this research:

Note: If you are proposing to undertake research which involves contact with children or vulnerable adults, you may need to hold a valid DBS (Disclosure and Barring Service, formerly Criminal Records Bureau – CRB) check. ***Where appropriate, please provide evidence of the check with your application.***
4. Please explain how you will determine your sample size/recruitment strategy, and identify, approach and recruit your participants. Please explain arrangements made for participants who may not adequately understand verbal explanations or written information in English. We aim to recruit 20 participants for this study. This will consist of students and staff within FET. Participants will be recruited by word-of-mouth and by email, being mentioned that no one is obliged to participate and that they can leave the study at any point without giving a reason. All participants will be fully briefed before undertaking any activity and given opportunity to ask questions.
5a. What are your arrangements for obtaining informed consent whether written, verbal or other? (where applicable, copies of participant information sheets and consent forms should be provided) All participants will be given a participant information sheet and a written consent form to complete. **b. What arrangements are in place for participants to withdraw from the study?** It will be explained to all participants that they have the right to withdraw during any stage of the investigation.
6. If the research generates personal data, please describe the arrangements for maintaining anonymity and confidentiality or the reasons for not doing so. The research will be undertaken anonymously, where only the video footage and joint position is recorded. Any work reported or published will be done anonymously. Any video data not deleted will be encrypted and stored securely.
7. Please describe how you will store data collected in the course of your research and maintain data protection. All collected data will be kept on an encrypted computer hard drive.
8. What risks (eg physical, psychological, social, legal or economic), if any, do the participants face in taking part in this research and how will you overcome these risks? Comfort and Hygiene considerations:

New pairs of gender neural shoes (Crocs) of 9 different sizes will be purchased for the experiments so that correct size shoes can be provided to each participant.

Disposable socks will also be provided to participants to ensure hygiene and similar surface friction.

A loose fitting coat will be used over existing clothing for the jacket dressing scenario.

The crocs will be sprayed with an antibacterial deodorant shoe spray between participants as in a bowling alley.

9 Are there any potential risks to researchers and any other people impacted by this study as a consequence of undertaking this proposal that are greater than those encountered in normal day to day life?

No

10 How will the results of the research be reported and disseminated?

(Select all that apply)

☒ **Peer reviewed journal**

☒ **Conference presentation**

☒ **Internal report**

☐ **Dissertation/Thesis**

☐ **Other publication**

☐ **Written feedback to research participants**

☒ **Presentation to participants or relevant community groups**

☒ **Other (Please specify below)**

May be reported to project sponsors

11 Are there any other ethical issues that have not been addressed which you would wish to bring to the attention of the Faculty and/or University Research Ethics Committee?

None

Checklist

Please complete before submitting the form.

	Yes/No
Is a copy of the research proposal attached?	Yes
Have you explained how you will select the participants?	Yes
Have you described the ethical issues related to the well-being of participants?	Yes
Have you considered health and safety issues for the participants and researchers?	Yes
Have you included details of data protection including data storage?	Yes
Have you described fully how you will maintain confidentiality?	Yes
Is a participant consent form attached?	Yes
Is a participant information sheet attached?	Yes
Is a copy of your questionnaire/topic guide attached?	Yes
Where applicable, is evidence of a current DBS (formerly CRB) check attached?	N/A

Declaration

The information contained in this application, including any accompanying information, is to the best of my knowledge, complete and correct. I have attempted to identify all risks related to the research that may arise in conducting this research and acknowledge my obligations and the right of the participants.

Principal Investigator name	Dr Greg Chance
Signature	[redacted]
Date	29/4/16
Supervisor or module leader name (where appropriate)	Dr Sanja Dogramadzi

Signature	[redacted]
Date	29/4/16

The signed form should be emailed to the Officer of the Research Ethics Committee (details at page 1) and email copied to the Supervisor/Director of Studies where applicable.

B.2.2 CS2 Amended Ethics Approval

Amendment to Existing Research Ethics Approval

Please complete this form if you wish to make an alteration or amendment to a study that has already been scrutinised and approved by the Faculty Research Ethics Committee and forward it electronically to the Officer of FREC (researchethics@uwe.ac.uk)

UWE research ethics reference number:	*FET.16.05.043*
Title of project:	Assistive interactive robotic system for support in dressing
Date of original approval:	*01/01/2018*
Researcher:	*Antonella Camilleri – Original Applicant for Ethical Form Dr. Greg Chance*
Supervisor (if applicable)	*Prof. Sanja Dogramadzi*

1. Proposed amendment: Please outline the proposed amendment to the existing approved proposal.

In the existing ethics approval, there are two parts of the experiment. In Part 1, participants interact with the robot to perform dressing. In Part 2, participants interact with the robot to perform dressing task 5 times while being distracted in different ways (cognitive loading game and conversation with the researcher). Part 1 and Part2 have already been approved by the ethical board.

This amendment is required to include additional interactions to the HRI dressing experiments. The user is to give commands to the robot while being dressed in order to proceed from one stage of the task to another.

2. Reason for amendment. Please state the reason for the proposed amendment.

The objective of this study is to evaluate alteration/changes in speech commands expected from the user when distractions during dressing interactions occur.
The proposed experiments will evaluate if this explicit interaction indicator can establish participants distractions. Interactions in previous experiments were passive (through force measurements).

3. Ethical issues. Please outline any ethical issues that arise from the amendment that have not already addressed in the original ethical approval. Please also state how these will be addressed.

General layout, equipment and measures of data collection remain unchanged to the original ones initially accepted.

Speech interaction will be recorded for the post-processing and will be treated as any other data collected in the experiments.

To be completed b[redacted]

Signature:	
Date:	

To be completed by Research Ethics Chair:

Send out for review:	☐ *Yes* ☒ *No*
Comments:	
Outcome:	☒ *Approve* ☐ *Approve subject to conditions* ☐ *Refer to Research Ethics Committee*
Date approved:	*11 October 2018*
Signature:	*Alistair Clark by email*

Guidance on notifying UREC/FREC of an amendment.
Your study was approved based on the information provided at the time of application. If the study design changes significantly, for example a new population is to be recruited, a different method of recruitment is planned, new or different methods of data collection are planned then you need to inform the REC and explain what the ethical implications might be. Significant changes in participant information sheets, consent forms should be notified to the REC for review with an explanation of the need for changes. Any other significant changes to the protocol with ethical implications should be submitted as substantial amendments to the original application. If you are unsure about whether or not notification of an amendment is necessary please consult your departmental ethics lead or Chair of FREC.

B.2.3 CS2 Consent Form

University of the West of England
BRISTOL

“Assistive interactive robotic system for support in dressing”

Research participant consent form

Please tick the boxes if the statements are true about yourself

Taking Part

I have read and understood the Information Sheet dated 09/10/2018. ☐

I have been given the opportunity to ask questions about the project, and have had my questions answered to my satisfaction. ☐

I ensure that I have no previous back injury. ☐

I ensure that I am not on any serious pain medication. ☐

I agree to take part in the project. Taking part in the project will include completing specific dressing tasks and giving vocal commands. ☐

I understand that some portions of the activities may be filmed. ☐

I understand that my taking part is voluntary; I can withdraw from the study at any time (up until the completion of the tests) and I do not have to give any reasons for why I no longer want to take part. ☐

Use of the information I provide for this project only

I understand my personal details such as phone number and address will not be recorded for any purpose or revealed to people outside the project. ☐

I am aware that data collected will be anonymous, kept in accordance with the data protection act, and will only be analysed by the research team as part of their studies. ☐

______________________________	________________________	_______________
Name of participant [printed]	Signature	Date

____

For researcher use only

Participant code: __________

______________________________	___________________________	_______________
Researcher [printed]	Signature	Date

Antonella Camilleri

Bristol Robotics Lab, T Block
University of the West of England
Frenchay Campus
Bristol
BS16 1QY

B.2.4 CS2 Information Sheet for Participants

University of the West of England
BRISTOL

Information Sheet for participants

Study:

Assistive Interactive robotic system for support in dressing

This research is being carried out as part of the EPSRC/CHIST-ERA funded I-DRESS project and SOCRATES project. The SOCRATES project has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement No 721619. The general aim of the project is that to improve interaction quality for older adults.

This research aims to determine what changes occur in verbal and non-verbal interactions (gestures, eye-gaze, body postures, adjustments and nudges) between a person and robot when distractions occur in these type of interactions. The objective is to find the common changes in used modalities when people are distracted while receiving a support in dressing from a robot by analysing a number of real dressing assistance scenarios. This data will then be used to build an interaction profile for a Human-Robot Interface to predict these unexpected events or distractions in an interaction.

The dressing tasks will be to put on a jacket. Participants will be fully clothed during the test although they will be asked to wear a motion tracking suit. During the exercise the pose, video and audio of the participants will be recorded.

We will be using an Xsens motion capture system (or similar) to record the position and motion of the participant. This will require the user to wear a thin bodysuit over their existing clothes. This is done to understand the movement of the person being dressed during the task. This motion will be recorded in a form or 3D coordinates (non-photographic). To record eye gaze in space, the Tobii Pro Glasses will be used to record.

The study includes taking a Task Load Index Questionnaire and two other questionnaires about the participant's level of trust and opinion of technology. This allows us to correlate our findings of robot interaction to user profiles in order to build more suitable robotic applications. The Task Load Index Questionnaire will be filled in between parts of the experiments.

Invitation:

We are researchers at the University of the West of England and are currently conducting a study into the interaction quality during a robotic-assisted dressing. We have developed this experiment to monitor what are the likely things a user might do when distracted during an assisted dressing task that they need. Particularly, we are interested in looking what are the dominant indicators of distractions in these type of close proximity interaction. The information obtained from this observation will be used in the development of robotic software that will give assistance in dressing tasks to people with mobility issues or those in rehabilitation.

In order to carry out the study we require participants to be recorded on video during an assisted dressing or a jacket. Before you decide whether you wish to accept the invitation or not, it is important for you to understand why the research is being conducted and what it will involve. Please take time to read the following information carefully and consult us if you have any queries or concerns, or if you would like more details.

If you do decide to take part, then you will be given this information sheet to keep and be asked to sign a consent form. You may decide not to continue with the study at any point up until the completion of the tests. You may do so without giving a reason.

Task:

If you decide to take part in the study, you need to follow this procedure. Instructions will be explained briefly through video demonstrations for participants.

The dressing experiment will be divided in 3 parts. The assistive daily living task of dressing task that represents a real, current need from carers and health professionals. The dressing support tasks will be that of putting on a jacket over existing clothing. Participants will be dressed by a robot; the robot will move slowly and have a limited range of motion. Participants are requested to wear light clothing, not baggy or warm clothes.

In part 1 and 2 of the experiment, we will aim to capture the non-verbal cues of the participant as they are being dressed. A researcher will be in constant attendance to assure the participant and ensure smooth running of the task. A lose fitting rain coat will be provided worn over existing clothing.

In part 2 a cognitive loading game will be displayed on a TV screen. Participant will have to speak out the position of the shapes on screen as a distraction while getting dressed by the Robot. Other distractions such as talking to the researcher and telephone ringing will be included in the experiment.

In part 3, a more active interaction will be offered to the participant. The participant need to give the go ahead of the robot to proceed in the dressing task. In this way the user will have more control over the interaction during the dressing task. The instructions from the participants need to be: “Go Ahead” to continue the dressing task; “Stop” to stop at any instance during the dressing task; “Completed” to acknowledge one of the three stages of the dressing task. The three stages of the dressing task will be: (1) dressing up to both hands, (2) dressing up to both elbows, (3) dressing up to both shoulders. During all the experiment parts, the dressing task will be repeated.

If you have any questions about any particular task, please do not hesitate to ask. Tasks will be observed by a researcher. You will also be filmed undertaking tasks so that the transcript can be obtained.

The information collected during the study will not contain any personal information about you beyond that provided on the consent form and information sheet. Where the experimental results are published, the data will be anonymised, no personal details will be included apart from your age and gender. If you would like access to any publications resulting from this work, then please contact us.

Safety:

You can stop your participation in the event at any point without needing to give any explanation. If your arms become fatigued during the test, please stop and rest immediately, you may continue at any point or if you wish you can simply cease the experiment.

Participants will be in close working proximity to a Baxter robot which is a collaborative robot with Series Elastic Actuators (SEA) that are inherently safer than standard servo driven robots. In the unlikely event that the robot will collide with you the elastic nature of the robot allows the limbs to flex instead of pushing the user. The robot will be moving slowly and will have a limited range of movement. If at any time there is an issue, there is an emergency stop button that can be used to stop the robot.

Confidentiality:

To ensure that participant confidentiality is maintained, all collected data will be kept on a partitioned encrypted hard drive. Any filming undertaken will be used to determine the vocabulary used during the dressing and to extract body position, stored as numbers only (non-photographic).

Antonella Camilleri
Bristol Robotics Lab, T Block
University of the West of England
Frenchay Campus
Bristol
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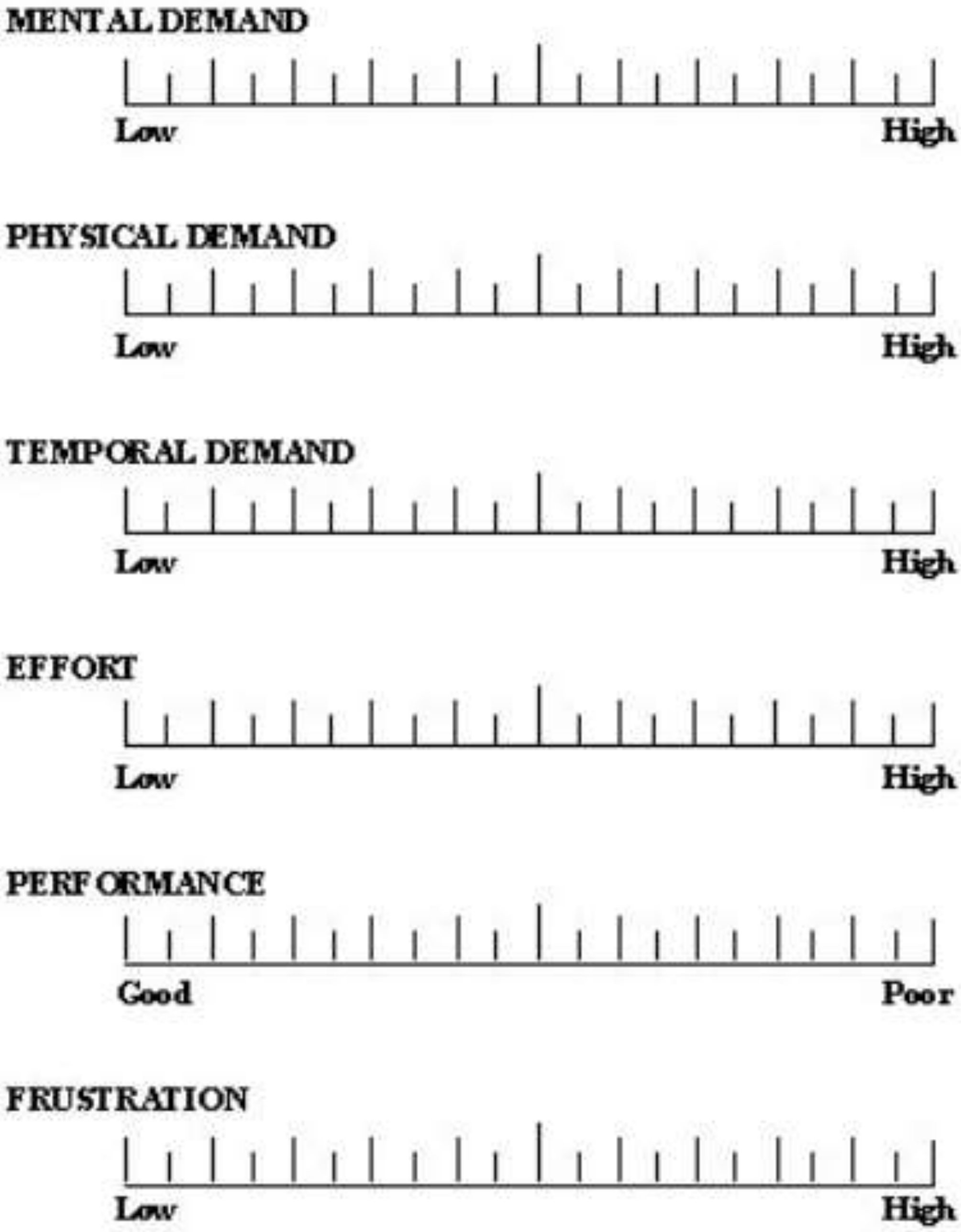
B.2.5 CS2 NASA Task Load Sheet

NASA Task Load Index



APPENDIX C

C.1 OS3: Observational Studies in Care Homes Ethical Approval and Additional Sheets/Forms

Due to Covid-19 Restrictions and Rules, this ethical approval was adopted for an observational study instead of hands-on experiments with older adults. The approach to the entire thesis and contributions was heavily impacted and had to be rethought and adjusted accordingly

C.1.1 OS3 Consent form for Carers

Consent Form Carer

You have been invited to take part in the SOCRATES project, as described in the Information Sheet, because we are interested in your views and experiences about the needs that people can have. This will help to shape the technology ideas being designed within the SOCRATE Safe Human Robot Interaction project.
Please read the following statements and only put your initials if you agree with the accompanying statement.

Only put your initials in each box if you agree with the accompanying statement

I have read and understood the information sheet ☐

I have been given enough time to decide whether I would like to participate, and have had the opportunity to ask any questions about the work ☐

I understand that my participation is entirely voluntary and I can withdraw my consent and stop participating at any time during the research session by letting a researcher know, without giving a reason ☐

Following discussion with the researcher about the different activities which are currently taking place, I agree to one or more of the following (as described on the Information Sheet):

(a) I agree to complete a screening questionnaire (attached to the information sheet) to ensure I can safely participate in an Assisted Daily Living Task study of outer layer dressing activity. ☐

(b) I agree to participate in an observation of an Assisted Daily Living Task study of outer layer dressing activity. ☐

(c) I agree to participate in an observation of an Assisted Daily Living Task study of shoe dressing. ☐

(d) I agree to wear the Xsens sensors shown in Figure 2: ☐

(e) I agree to wear the Tobii Pro Glasses Eye Tracker shown in Figure 1 ☐

(f) I understand that any identifiable information about me (e.g. name, personal details) will remain strictly confidential and won't be used outside the project, and that any research data will be anonymized ☐

(g) I understand that this activity will be video recorded and will remain strictly confidential and won't be used outside the project, and that any research data will be anonymized

(h) I understand that I may withdraw my data from the study up to 7 days after I have taken part in a session by contacting the Principal Investigator

(i) I understand that anyone with a pacemaker cannot participate in these experiments. I can confirm that I do not have a pacemaker.

Participant signature…………………………………………………… Date………………………………….

Participant signature……………………………………………………………………………………….

Researcher name……………………………………………………….. Date……………………………….

Researcher signature………………………………………………………………………………………

Xsens Sensors – Sensors on velcro bands attached over clothes (just under knees, on thighs, arms) and on a head band.

Figure 1 - Xsens Suit

Figure 2 - Tobii Pro Glasses Eye Tracker

C.1.2 OS3 Consent form for Older Adults

SOCRATES
Social Cognitive Robotics
in The European Society

Consent Form - Older Adults

You have been invited to take part in the SOCRATES project, as described in the Information Sheet, because we are interested in your views and experiences about the needs that people can have. This will help to shape the technology ideas being designed within the SOCRATE Safe Human Robot Interaction project.
Please read the following statements and only put your initials if you agree with the accompanying statement.

Only put your initials in each box if you agree with the accompanying statement

I have read and understood the information sheet ☐

I have been given enough time to decide whether I would like to participate, and have had the opportunity to ask any questions about the work ☐

I understand that my participation is entirely voluntary and I can withdraw my consent and stop participating at any time during the research session by letting a researcher know, without giving a reason ☐

Following discussion with the researcher about the different activities which are currently taking place, I agree to one or more of the following (as described on the Information Sheet):

(a) I agree to complete a screening questionnaire (attached to the information sheet) to ensure I can safely participate in an Assisted Daily Living Task study of outer layer dressing activity. ☐

(b) I agree to participate in an observation of an Assisted Daily Living Task study of outer layer dressing activity. ☐

(c) I agree to participate in an observation of an Assisted Daily Living Task study of shoe dressing. ☐

(d) I agree to wear the Xsens sensors shown in Figure 2: ☐

(e) I agree to wear the Tobii Pro Glasses Eye Tracker shown in Figure 1: ☐

(f) I understand that any identifiable information about me (e.g. name, personal details) will remain strictly confidential and won't be used outside the project, and that any research data will be anonymized ☐

UWE Bristol University of the West of England

(g) I understand that this activity will be video recorded and will remain strictly confidential and won't be used outside the project, and that any research data will be anonymized ☐

(h) I understand that I may withdraw my data from the study up to 7 days after I have taken part in a session by contacting the Principal Investigator ☐

(i)I understand that anyone with a pacemaker cannot participate in these experiments. I can confirm that I do not have a pacemaker. ☐

Participant signature………………………………………………… Date……………………………….

Participant signature……………………………………………………………………………………….

Researcher name……………………………………………………… Date……………………………….

Researcher signature…………………………………………………………………………………………

Xsens Sensors – Sensors on velcro bands attached over clothes (just under knees, on thighs, arms) and on a head band.

Figure 2 - Xsens Suit

Figure 1 - Tobii Pro Glasses Eye Tracker

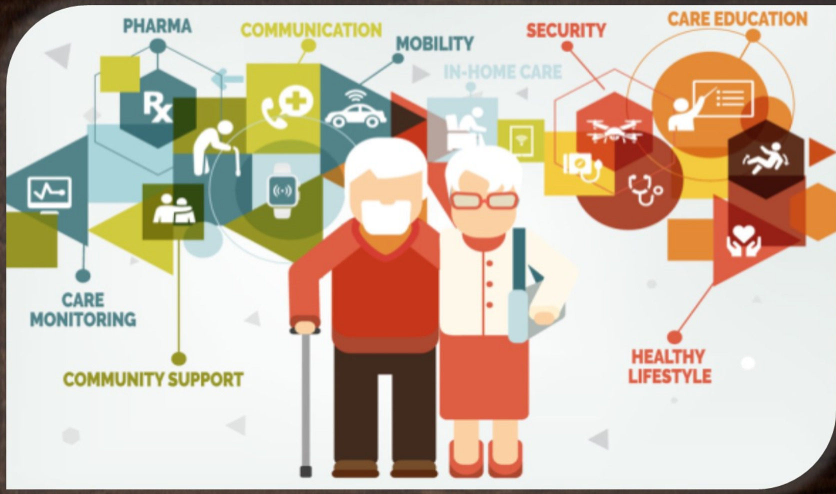
C.1.3 OS3 Poster for Care Home and Older Adults

Care Homes Safety Study

Technology advances are paving the way for older adults for active aging at homes. This can be achieved by providing assistive help required while carrying out the daily living tasks.

However, to provide solutions to daily problems; knowledge and awareness of the context, procedures, and effort required to perform this daily task are vital.

This observational study will help to understand better the necessities and context evolving around the daily assistive tasks performed in care homes. From the research accept, this will help to develop a more practical framework for safe human-robot interactions.



Improving Human Robot Interaction Quality for Older Adults

The Assistive Daily Living Task of dressing will be observed. Posture movement of the carers and adults will be recording through data collected from an Xsens suit.

The data from the suit will be used to analyze movements involved into completing this dressing task.

HELP US!

To participate in this study, contact Antonella Camilleri at Bristol Robotics Laboratory on antonella.camilleri@brl.ac.uk

This study is part of a project SOCRATES[1] coordinated by the European Commission, funded by EC under grant agreement No 721619

[1] http://www.socrates-project.eu/

C.1.4 OS3 Ethics Approval Risk Assessment

GENERAL RISK ASSESSMENT FORM

Ref:

Describe the activity being assessed: Observation of Assisted Daily Living Task in Care Homes.	Assessed by: Antonella Camilleri	Endorsed by: Dr Sanja Dogramadzi	Endorsed by (name of programme manager or designate):
Who might be harmed: Fully informed and consenting adult (18yrs+) participants How many exposed to risk: All participants	Date of Assessment: 5th September 2018	Review date(s):	Review date(s):

Hazards Identified *(state the potential harm)*	Existing Control Measures	S	L	Risk Level	Additional Control Measures	S	L	Risk Level	By whom and by when	Date completed
Risks to Participant – Older Adult - Issues due to Xsens Suit during task observations.										
Strain [1]	1. Strain There is no risk for the participants to experience more strain than usually exhibited. Participants will not be instructed on how to do the task. The older adults and carer will only be observed to do the daily assistive task in the typical and normal environment of their care home as it is ordinarily preformed. They will also be reminded of this at the start of the study.	1	1	1						
- Fatigue [2]	2. Fatigue Participants will not be instructed on how to do the task. The older adults and carer will only be observed to do the daily assistive task in the typical and normal environment of their care home. Participants will also be reminded that they can take other breaks at any time.	1	1	1						

	Participants will be reminded that they are able to withdraw from the study at any point, so if they do feel fatigued and are unable to continue effectively, they are welcome to stop the observations.									
- Physical Mobility [3]	3.Physical Mobility All sensors will be attached in an appropriate manner and will not restrict movement in any way. Xsens suit is designed to record movement so sensors are themselves designed to not restrict movement at all. If older adult feel uncomfortable than Xsens suit will only be worn by Carer.	1	1	1						
- Additional age related factors [4]	Typical protocols used by carers to prevent fatigue will not be restricted or instructed otherwise.	1	1	1						
- Other equipment in the room.	The room in which the study will be conducted will not be altered or changed.	1	1	1						
Risks to Participant – Carer Issues due to Xsens Suit during task observations. - Strain [1]	 1. Strain There is no risk for the participants to experience more strain than usually exhibited. Participants will not be instructed on how to do the task. The older adults and carer will only be observed to do the daily assistive task in the typical and normal environment of their care home as it is ordinarily preformed. They will also be reminded of this at the start of the study.	1	1	1						

- Fatigue [2]	2. Fatigue Participants will not be instructed on how to do the task. The older adults and carer will only be observed to do the daily assistive task in the typical and normal environment of their care home. Participants will also be reminded that they can take other breaks at any time. Participants will be reminded that they are able to withdraw from the study at any point, so if they do feel fatigued and are unable to continue effectively, they are welcome to stop the observations.	1	1	1						
- Physical Mobility [3]	3.Physical Mobility All sensors will be attached in an appropriate manner and will not restrict movement in any way. Xsens suit is designed to record movement so sensors are themselves designed to not restrict movement at all. Carer's physical mobility and ability to take care of the older adult will not be restricted by the Xsens suit	1	1	1						
- Additional age related factors [4]	Typical protocols used by carers to prevent fatigue will not be restricted or instructed otherwise.	1	1	1						
- Other equipment in the room.	The room in which the study will be conducted will not be altered or changed.	1	1	1						
Risk to researchers	There are no envisaged risks to the researchers in these studies									

RISK MATRIX: (To generate the risk level).

Very likely 5	5	10	15	20	25
Likely 4	4	8	12	16	20
Possible 3	3	6	9	12	15
Unlikely 2	2	4	6	8	10
Extremely unlikely 1	1	2	3	4	5
Likelihood (L) ↑ / Severity (S) →	Minor injury – No first aid treatment required 1	Minor injury – Requires First Aid Treatment 2	Injury - requires GP treatment or Hospital attendance 3	Major Injury 4	Fatality 5

ACTION LEVEL: (To identify what action needs to be taken).

POINTS:	RISK LEVEL:	ACTION:
1 – 2	NEGLIGIBLE	No further action is necessary.
3 – 5	TOLERABLE	Where possible, reduce the risk further
6 - 12	MODERATE	Additional control measures are required
15 – 16	HIGH	Immediate action is necessary
20 - 25	INTOLERABLE	Stop the activity/ do not start the activity

Glossary

Close-Proximity Collaborative Interaction An interaction that requires a robot to move very close to the human or vice versa. The interaction workspace is directly around the end user and, in some cases, the user itself. The actions of the robot and human are simultaneous, not sequential. Physically Assistive Tasks require close-proximity collaborative interactions before a physically assistive task can take place.. 313

Case Study 1 Evaluation of human movement during a socially assistive task. A dataset of human movement performing actions required to interact with a socially assistive robot is recorded. 313

Case Study 2 Evaluation of human movement during a physically assistive task. Recorded within a dynamic environment, a dataset captures the human movement involved in a robot-assisted dressing task. 313

Human State This term in HRI refers to a general term that describes the current cognitive and emotional state of the human during the interaction. The human state can vary between different persons and situations, and therefore, it can fluctuate during the interaction. Human Factor directly impacts the human states and the metrics of human-robot interaction, meaning that the context of interaction and robot's behaviour can impact the human state. Other terms used to describe the human state in literature are: acceptance, fatigue, stress, frustration, trust, safety, mental, exhaustion, anxiety, arousal, cognition, workload, sleep, psychological, user state, and awareness [72]. 311, 314

NASA-Task Load Index This is a questionnaire used to provide an index about the individual's perceived workload based on six subjective sub-scales. The questionnaire can be found in Appendix B. 314

Observation Study 3 Evaluation of carers' interaction and assistance with older adults. Observations were conducted in care homes to evaluate the approach for assistive tasks in a real-context environment. 314

Probabilistic Movement Primitives Probabilistic Movement Primitives is the learning to model and generate movement trajectories as a distribution over trajectories. This allows uncertainty and variant in the execution o movement to be considered. Learning is done from observed demonstrations whereas the new generation can take the underlying structure of the trajectories and allow for deviations and adaptation in a real-context environment. 314

Unexpected Events The occurrence of any form of distraction from the surrounding environment or from the user itself that can hinder the planned interaction between the human and robot. 315

Assistive Human-Robot Interaction is an interaction with the aim of assisting people in need by helping them finish a task by enriching the quality of life of individuals with disabilities or other impairments. The assistance can be social, cognitive or physical. Assistive robots require their designs, control and sense to support a human-in-the-loop to provide one of the three types of assistance. Assistive Human-Robot Interaction is a type of cHRI with a different focus since the goal is to complete a task required by the human, not a task assigned to both the human and the robot. 313

Collaborative Human-Robot Interaction is an interaction that aims to improve the task's efficiency, productivity and safety whilst collaborating with a human in an industrial or manufacturing setting. Collaborative robots need to detect and adapt to the actions and movements of human workers to avoid collisions and ensure that the tasks are performed accurately and efficiently. The efficiency of the task is achieved through the combination of the robots' accuracy and complex processing capabilities with human knowledge and dexterity. In literature, Human-Robot Collaboration (HRC) is sometimes used instead of cHRI; however, in this thesis, we want to highlight that only some interactions can have continuous collaboration and that, in some instances, collaboration is lost during interaction. 313

Human Factors The main categories that make up Human Factor are (i) mental factors (memory, reasoning, learning, knowledge, training, experience/s, behavio(u)r/al, competencies, creativity, psychology, cognitive load and communication impact on decision making), (ii) physical factors (safety, motor skills, ergonomics, fatigue, posture, well-being, gesture, musculoskeletal disorder and training), (iii) psychology (trust, stress, emotions, feedback, motivation, task demand, task control, teamwork, culture and acceptance) and (iv) perceptual (spatial awareness, information processing, perception and reaction) [63, 72, 111, 142]. These factors affect how the human sees the robot and determines if the interaction/collaboration are effective or not. Designing HRI based on these factors will ensure that all Human State needs to make interaction successful. 309, 310, 313

Physically Assistive Robots a device or tool capable of helping individuals through physical interaction. PARs can sense, process sensory information, and perform actions to support the autonomy of potential user by allowing them to carry out the tasks by themselves without the help of a human carer in the course of their daily living. 311, 314

Pertinence of Robot Decisions in JoinT Action This questionnaire aims to assess the user experience by examining the consequence of a participant's internal sate, the characteristics of the designed system and the contextual factors of the environment in which the interaction occurs. 311, 314

Proximate Human-Robot Interaction is a complex subspace within human-robot interaction since it refers to social, cognitive and physical HRI that are in close proximity to each other. pxHRI can include physical contact, such as when the human touches the robot, and non-physical interactions, such as when the human uses speech or gestures to interact. Research in this space involves a range of robot systems and methods that require precisely sensing humans such that the robot interacts in a collaborative and intuitive manner. aHRI and cHRI are both proximate human-robot interactions. 22, 314

Acronyms

aHRI Assistive Human-Robot Interaction. 18–22, 25, 27, 33, 35, 43–45, 48, 62, 87–92, 114, 115, 117, 118, 121, 122, 125, 126, 149, 150, 157, 161, 165–167, 169, 171, 172, 175, 177, 179, 180, 182, 183, 185, 186, 310, 311

cHRI Collaborative Human-Robot Interaction. 18–21, 31, 35, 44, 93, 171, 310, 311

CPCI Close-Proximity Collaborative Interaction. 3, 27, 31, 92, 114, 116, 149, 151, 153, 157, 176, 177, 185, 309

CS1 Case Study 1. 10, 11, 13, 23, 26, 43, 49, 56, 62, 67, 78, 87–89, 91, 122, 158, 171–173, 182, 309

CS2 Case Study 2. 10, 11, 13, 14, 23–27, 32–34, 37, 88, 90, 92, 96, 114, 116–119, 122, 126, 146, 149, 150, 152–155, 158, 160, 161, 166, 167, 170, 171, 173, 174, 176, 177, 179–181, 183, 309

ESR Early Stage Researcher. 47

FHA Functional Hazard Assessment. 126–128

FMECA Failure Mode, Effects and Criticality Analysis. 126, 127

FTA Fault Tree Analysis. 126, 127

HAZOP Hazard Operability Analysis. 126–129, 131

HF Human Factor. 18–20, 27, 38–40, 47, 88, 90, 92, 114, 144, 169, 173, 177

HM Human Movement. 6

HRC Human-Robot Collaboration. 6

HRI Human-Robot Interaction. 2, 4, 6, 10–12, 14, 17, 18, 22, 23, 25–27, 31, 37, 46, 123, 142, 174, 178, 185, 309, 311

HS Human State. 4, 19–21, 27, 38–40, 47, 88, 90, 92, 114, 115, 144, 158, 168, 169, 173, 175, 177, 179, 309

I4.0 Industry 4.0. 18

I5.0 Industry 5.0. 18

NASA NASA-Task Load Index. 94, 101, 107, 108, 114, 115, 174, 175, 309

OS3 Case Study 3. 12, 14, 23–25, 27, 32, 33, 90, 121, 122, 132, 144, 161, 170, 171, 177, 183, 310

PAR Physically Assistive Robots. 17, 20, 39

PBS Persona-Behavior Simulator. 46

PD Persona Definition. 46

PeRDITA NASA-Task Load Index. 94, 102, 104, 114, 115, 174, 175

PHA Preliminary Hazard Analysis. 126

pHRI physical Human-Robot Interaction. 36, 92–94, 96, 122, 125, 126, 143, 144

ProMP Probabilistic Movement Primitives. xiii, xvi, 31, 61–63, 74–81, 84, 85, 87, 88, 172, 310

pxHRI Proximate Human-Robot Interaction. 22, 125, 151, 311

RFID Radio Frequency Identification. 45, 47

SARA Social Assistive Robotic Agent. 43, 45–47

SHARD Software Hazard Analysis and Resolution in Design. 126, 129

SOCRATES Social Cognitive Robot Agents in The European Society. 7, 47

STPA Systems Theoretic Hazard Analysis. 126, 129, 130

TE Task Engine. 46, 47

UnEv Unexpected Events. 2, 310

WHO World Health Organization. 18, 38

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