A Biologically Inspired Cognitive Intelligence with Stress Based Modelling and Working Memory Optimisation for Robot Partners

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This thesis is dedicated to my wonderful wife
Stephanie
for her love and support.

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Abstract

This thesis addresses one of the fundamental questions for any ageing society: Who will care for the elderly? The "who" is shaping up to be the highly advanced technology in the area of humanoid robotics. The advantage of humanoid robots is that they can be designed to look and act like humans, but how do we avoid "uncanny valley", where people reject humanoid robots in the long run for "looking human", but not "behaving human"? It raises an important question of how we make robots that behave more humanlike, so our ageing societies readily accept them. Critically, how do we advance a robot's *embodied cognitive intelligence*?

We identify three key components behind the idea of embodied cognitive intelligence: Spiking Neural Network (SNN), working memory and stress response system. The stress response system acts to moderate working memory function, and together they help to encode and summarise a robot's current environment context information which can be used to optimise available actions, plans and intentions. Meanwhile, the SNN activation will determine the timing of new intuition creation. The ability to understand something immediately, without the need for conscious reasoning. In our model, the outputs of the SNN are defined as intuition.

In the first part of this thesis, we explore the idea of working memory and how it is regulated and optimised within biological systems in a Markov Decision Process (MDP) navigation problem. One of the key theories in this area is from Lupien, who demonstrated that stress hormones play a critical role in governing the function of working memory during some uncertainty in the environment. We develop a working memory model based on their stress theories. Our model allows the robot to "focus" on a particular set of actions at any given moment according to the currently

perceived environment context information. It enables our model to address the combinatorial explosion problem normally associated with large action sets and allows us to extend standard Q-Learning techniques to enable the robot to select near-optimal actions in real time.

In the second part, we address another working memory characteristic, first identified by the cognitive psychologist Braver that he termed *dual mechanisms of cognitive control*. *Proactive control* is one of the cognitive control mechanisms whereby a robot's environment context information is fed back into working memory as an input to enable active working memory optimisation towards some intention. We model this proactive control behaviour using two novels biologically inspired genetic algorithm approaches. Next, we validate our proposed spiking reflective processing model that leads to agent's creation of new intuition with established psychology tests.

We validate our model with an interactive human-robot conversation scenario. Our survey from the human-robot interactive scenarios shows that the proposed model is evaluated to be more human-like in behaviour during human-robot interaction and a few steps closer to our ultimate goal.

Contents

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Chapter 1

Introduction

1.1 Chapter Introduction

This chapter shows an overall introduction to the Ph.D. research. Firstly, this research questions are posed, and then we discuss the problems of elderly people in an ageing nation in detail. Furthermore, we define the concept of robot partner and issues concerning elderly people. Next, we discussed our motivations behind this research in the following section.

Definition 1.1.1. *Robot partner* is an intelligence robot that works, operates, survives and communicates with its human user as well as with another robot partner. We also define a human's companion robot as a robot partner.

Subsequently, an overview of this research is explained with a diagram. Finally, the research motivation, hypothesis and objective to support the elderly people are in the final sections of this chapter.

1.2 The Ageing Nations' Challenges

In developed nations the total elderly people population consists of a high percentage in ageing society. For example for the year 2013, the elderly population in Japan (65 years and above) was recorded for 31.9 million people. The statistics report [158] indicated the elderly people consisting of an enormous percentage of 25.1% of the total population. In other words, the current Japan population includes one elderly person for every four individuals, a world record for the largest elderly population as shown by the United Nations Statistics Bureau, Ministry of Health Labour and Welfare (Figure 1.1). In this research context, the Japanese ageing phenomenon is the focus of this research context because of its severity in ageing problems. However, the research outcome can be applied to different ageing nations. Moreover, the robot partner solution is especially emphasised in the Japanese context because of its government supports for the human labour shortage in industrial and elderly care sectors (sector 1.3). Furthermore, Japanese's cultures, religious and philosophical doctrines did not impede the acceptance of robot partner solution as compared to western countries [107].

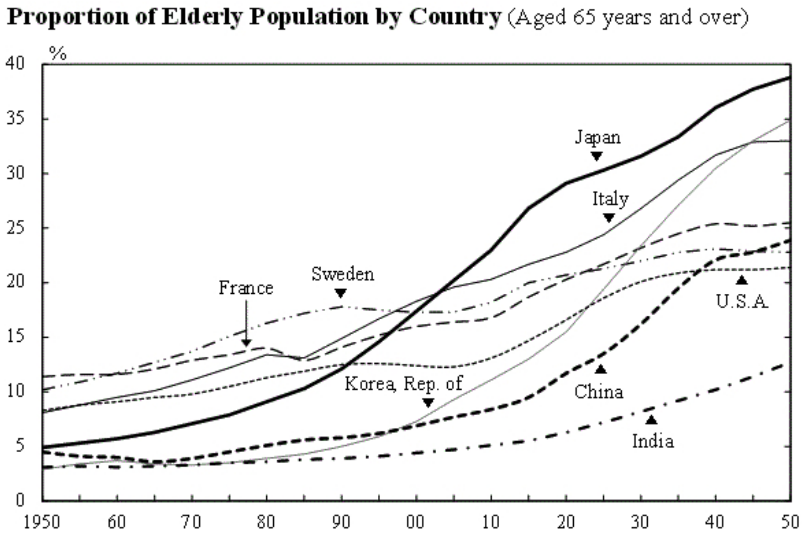


Figure 1.1: Proportions of Elderly Population by Country. *Source: Statistic Information, Statistics Bureau, Ministry of Health, Labour and Welfare, United Nations [158]. The permission of the content reuse was granted based on the term of use on the website.*

In addition to that, Japan's population is ageing much faster compared with those of other developed western European countries or the United States of America [158]. For example, the elderly population in Japan during in 1970 only consisted of 7.1% of the total population, but after 24 years in 1994, the percentage of the elderly people had doubled to 14.1%. It is a record incremental rate regarding ageing when compared with other nations aged population; for example, Italy needed 61 years, Sweden 85 years and France 115 years for the same percentage increment from 7 to 14% of the elderly population. Comparison of the different ageing rates emphasises the rapid ageing development in Japan.

Furthermore, the child population (from the newly born to 14 years old) in the year 2013 at Japan reached only 16.39 million individuals (Figure 1.2), at 12.9% of the total population in Japan. It was also the lowest child birth rate ever recorded in

Age Structure of Population by Country

(%)

Country	2010			2050 (projection)		
	0-14 years	15-64	65 and over	0-14 years	15-64	65 and over
Japan	13.2	63.8	23.0	9.7	51.5	38.8
Korea, Rep. of	16.2	72.7	11.1	12.0	53.1	34.9
Italy	14.0	65.7	20.3	13.9	53.1	33.0
Germany	13.4	65.8	20.8	12.6	54.7	32.7
France	18.4	64.8	16.8	17.0	57.6	25.5
U.K.	17.6	65.9	16.6	16.6	58.7	24.7
Canada	16.5	69.4	14.2	16.5	58.8	24.7
China	18.1	73.5	8.4	14.7	61.3	23.9
Sweden	16.5	65.3	18.2	18.0	59.2	22.8
Brazil	25.5	67.6	6.9	15.3	62.2	22.5
U.S.A.	19.8	67.1	13.1	18.2	60.4	21.4
Russia	14.9	72.0	13.1	17.1	62.4	20.5
India	30.2	64.8	5.1	19.5	67.8	12.7

Figure 1.2: Age Structure of Elderly Population by Country. *Source: Statistics Information, Statistics Bureau, Ministry of Health, Labour and Welfare, United Nations [158]. The permission of the content reuse was granted based on the term of use on the website.*

the world. In another point of view, the elderly population had surpassed the child population since 1997.

To address research question 1, RQ1 (subsection 1.7.1), Japan's ageing phenomenon has given rise to the following issues:

1.2.1 Social Isolation

In traditional Japanese culture, the eldest son, daughter or daughters-in-law have the responsibility to take care of the elderly family members. However, due to modernisation and deterioration of the social values of Japanese society, such practice can not always be fulfilled [112]. The reason is the eldest son, daughter or daughters-in-law of the elderly people may be working. As a result, the younger generation may not able to take care of their parents or parents-in-laws. The Japanese government has identified these problems by setting up many nursing homes and home health programme for the elderly people in recognising these new social development trends. Thus, many elderly people are living alone in nursing homes and separated from their children and relatives. Although they are physically taken care of in these homes, they are socially isolated from their family members. This isolation can create many social problems in the ageing society, problems that can intensify when they suffer from physical immobility. Common are the elderly people with problems in walking. Some of these elderly people are reported to be suicidal to ease their suffering, having lost their motivation to live [112].

In sum, these elderly people are very lonely individuals and in constant need of companionship. Robot partner can provide companionship and real-time video conference technology with their family members to ease their social needs.

1.2.2 Mental Health Issues

In addition to social isolation issues, elderly people may be subjected to mental diseases such as dementia and Alzheimer's disease. The ageing effects of the elderly people cause these mental health problems. They need constant interactions to stimulate their brains to reduce the risk of these mental diseases. The robot partner solution can provide constant conversational interactions to them. Furthermore, the robot partner can also provide frequent news updates, social media and telepresence to the elderly people to stimulate their minds to reduce the risk of dementia and Alzheimer's disease [51, 56, 181].

1.2.3 Physical Health Issues

Elderly people may experience mobility issues during their ageing progress. For example, an elderly people cannot answer a phone call due to his or her mobility limitation. On top of that, the elderly people may be reluctant to exercise because of their limited mobility or pain associated with mobility. The robot partner solution can provide exercise training to the elderly people. Furthermore, the robot partner can act as a telepresence communication devices for them to reduce their mobility requirement.

1.2.4 Lack of Human Resource in Nursing Homes

The decline of the young workforce in many sectors in Japan challenges the country's economic sustainability. The lack of human resource plus the reluctance of young Japanese to take up nursing career affect the ageing society in many ways. The robot partner can act as a sensor to monitor the elderly people's health conditions. On top of that, the robot partner can complement some of the tasks of the care workers [112]. For example, the robot partner can partly substitute social welfare workers with the human-robot verbal conversation with elderly such as telling jokes, announcing news and telling stories.

1.2.5 Effectiveness of Early Health Warning System

In this work [166], an early health warning system is proposed to save the elderly people's lives, for example, for emergency events such as heart attack or stroke. However, for the early health warning system to be practical, the system needs to confirm the health signals before sending out warning messages. The robot partner acts as the confirmation vehicle before sending out the health alert signals. For example, the robot partner may ask "Are you okay?" and other health diagnostic questions to the elderly people. The elderly people may respond to indicate their need for help, or may be too weak to answer. Consequently, after asking a few times without getting any reply, the robot partner sends out the health warning signals to the health workers in advance to save the elderly's life. The robot partner also acts as the monitor system to monitor the lifestyle changes in the elderly people.

Furthermore, in an emergency event such as a stroke, the elderly people also need a constant reminder to stay awake, this is to ensure survival because if he or she may fall into sleep, resulting in coma or death. The robot partner can act as the agent to constantly remind the elderly people to stay awake until the health personnel come to the rescue.

1.3 Robot Partner Solutions

On 11 September 2014, Japanese Prime Minister Shinzo Abe initiated in Japan the world first Robotic Revolution Initiative Council to draw a 5-year plan for the robotic revolution initiative [130]. The ultimate goal is to set targets to increase the robot market size.

The Robotic Revolution Initiative Council's target is to double the monetary support to the use of robots in manufacturing. Also, the initiative will increase 20-fold support in non-manufacturing robotics in the service sectors (home companion robots or robot partners). The Robotic Revolution Initiative Council's main intention is to make Japan the world-leading nation in robot technology.

1.4 What are the Perceived Limitations of Current Robot Partner Solutions?

Although the robot partner solution is receiving support from the Japanese government for the next five years, the robot partner solution still has fundamental issues to be solved. The BBC has reported negative feedback on robot partner application from Japanese elderly users. For example, one user replied that he wanted a human to take care of him. Furthermore, another user responded, "Japan has yet to create any commercially successful home robot" says Yukihiro Goto, a medical tech analyst at Macquarie Japan [52].

The first point is very telling, the user "wanted a human to take care of him", but what does this mean exactly? Does this mean the user looks to a human to care for him? Alternatively, perhaps the user simply wants to be taken care of by human qualities? We do not know, but for this research, we assume the latter, and that a robot with human qualities will meet this user' needs and requirements.

So the next question is, what is it to be human and have human-like qualities? It is the type of question that we still do not have a definitive answer yet. Of the many aspects of this issue, we focus on the notion of "intelligence". The reason is although numerous research studies had investigated the user acceptance of robot partner applications [16, 50, 71, 72, 154, 187]. However, these studies had not specifically investigate the user acceptance in the perspective of robot partner with human-like (biological) intelligence properties. We will investigate the user acceptance of our proposed spiking reflective processing model in Chapter 7 with established psychology questionnaire evaluation. Therefore in the next section, we explore the idea of intelligence further that will lead us to our research questions on robot partner and its acceptance in ageing society.

1.5 What is Intelligence?

Definition 1.5.1. *Intelligence* is the ability to survive [135].

According to Pfeifer's view on intelligence [135], intelligent behaviour does not belong to certain organism species or artificial life. He named the organism species or artificial life that exhibit intelligence as agent (definition 1.6.4). The important point he made is the agent can exhibit the intelligence behaviours and the intelligence researcher can understand and generalise these behaviours to a broad range of other agent's behaviours. This research supports the Pfeifer's view on intelligence and we quoted his statements on intelligence.

> A precise characterization of intelligence is not all that essential to understanding it. Rather than debating whether a particular behaviour should be called intelligent or not, it is a point that is always debatable. We attempt to answer the next question, for an example given some behaviour–say of a human, an ant, an elephant, or a robot that we find interesting in some ways, how does the behaviour be created? If we managed to

> provide sound answers to this question for a broad range of behaviours, only then we reached an understanding of the principles underlying intelligence [135].

Definition 1.5.2. Emotional Intelligence (EI) or Emotional Quotient (EQ) is the ability to recognise one's own and other people's emotions, to distinguish between various feelings and label them appropriately, and to use emotional information to guide thinking and behaviour [36].

The robot partner's Emotional Intelligence (EI) is crucial for human-robot interactions. In Chapter 7, our proposed robot partner's communication model is equipped EI to understand the user's emotions by analysing the user's spoken words. Our initial experimental result indicated valuable user's feedback about our proposed model after the human-robot interactions experiment.

1.6 What is Cognitive Intelligence?

The modern and consolidated definition of *cognitive intelligence* first appeared in the Wall Street Journal editorial that was signed by 52 intelligence researchers in 1994 [65]. The following is the definition of cognitive intelligence to address partially the research question 2, RQ2 (subsection 1.7.2). We will formally define embodied cognitive intelligence for RQ2 at the end of this section:

Definition 1.6.1. *Cognitive Intelligence (CI)* is a mental capability that involves the ability to reason, plan, think abstractly, solve problems, learn quickly, comprehend complex ideas and learn from experience. It is not merely book learning, test-taking smarts, or a narrow academic skill. Rather, it reflects a deeper and broader capability for comprehending our surroundings such as making sense of things, catching on, or figuring out what to do [65].

The Cognitive Intelligence (CI) definition (definition 1.6.1) [65] focus on the core aspects of the agent's ability to plan, reason, and use of logical deduction to solve problems. For example, the agent's ability to plan and find the shortest path in a navigation problem (Chapter 3). Another intelligence behaviour example is agent's ability to reason by creating new intuition (making sense of things) about the perceived environment information (Chapter 7). Furthermore, CI enables the updates of agent's working memory that is optimisation toward its intention as discussed in Chapter 4.

To address the current limitation of user acceptance for the robot partner solution in this research's assumption (section 1.4), the term Cognitive Intelligence (CI) or Intelligence Quotient (IQ) needed to be rigorously examined and understood. We divided the term CI into two sub-terms and they are cognition (definition 1.6.2) and intelligence (definition 1.6.3). Then, we list the chronological table (Table 1.1) of CI research history in this section [59, 123]. Finally, we discuss the modern CI definitions and its relation to this study.

Definition 1.6.2. Cognition is the action or ability of knowing taken in its widest sense, including sensation, perception and conception. It is different from volition and feeling; also, more specifically, the action of cognizing an object in perception proper [41].

Definition 1.6.3. Intelligence is having a good measure of understanding; quick to understand; knowing, sagacious [42].

Table 1.1 shows that modern cognitive intelligence studies emphasise the importance of a broad range of cognitive intelligence's components consideration for cognitive psychology research study [126, 127]. For example components such as attention, utilisation of knowledge, generation of knowledge, perceptions, natural environment settings, working memory retrieval performance, stress emotion, judgement, affordance, evaluation, reasoning, computation, problem-solving, comprehension and production of language [59, 62, 104, 123, 126, 127]. It is a contrast to early cognitive intelligence research that only focused on limited numbers of cognitive intelligence's components [123]. Furthermore, these early studies did not emphasise the importance of natural environment settings and memory construction factors for experiment [1, 126, 127, 139].

Due to the recent cognitive intelligence studies that stress on comprehensive perceptions analysis with natural environment settings and memory constructions (new intuition creation) process [62, 126, 127] (Table 1.1). Therefore, we preferred the modern understanding of cognitive intelligence as our core view that focuses on comprehensive perceptions analysis in working memory with natural environment settings.

> Working memory (WM) is the set of mental processes retain limited information in a temporarily open state in service of *cognition.* The WM measures that have yielded high similarities with aptitudes include separate storage-and-processing task components, on the assumption that WM involves both *processing* and *storage* [39].

Working memory is needed to store *situation* information of the currently perceived environmental information. Furthermore, our research also focuses on new *intention* creation process with perceived perceptions from the natural environment settings in the working memory [104] of robot partner. As an example, we quoted Cowan's work on the working memory and its relation to cognitive intelligence [39].

Recent cognitive psychology research studies [8, 26, 39] had shown many empirical results in the correlation between working memory and cognitive intelligence. In other words, working memory is the key component of cognitive intelligence behaviour. As discussed in Chapter 6, it is because working memory stores the perceived perceptions of the natural environment settings and then constructs the stored perceptions in the working memory into new intention. On top of that, we proposed spiking reflective processing model (Chapter 7) of robot partner's artificial stress hormone that regulates the working memory retrieval performance [104] for working memory optimisation and new intuition creation process.

Cognitive intelligence is a subcategory of intelligence; therefore, some researchers refer them as the same definition because they are highly related. For example, intelligence is the capacity to exhibit survival behaviours of an agent [135]; cognitive intelligence is the ability to exhibit survival behaviour that uses perceived perceptions [41] to construct new intuition to react to its environment [42]. Hence, cognitive intelligence is a more detailed explanation of intelligence behaviours.

Definition 1.6.4. *Agent* is a living organism or artificial life that exhibits intelligent behaviours [135].

However Pfeifer's intelligence definition 1.5.1 is an abstract definition because survival skills involve communication skills, skill acquisitions, skill application, social skills and adaptation skills to the unknown environment [135]. Therefore, his view of cognitive intelligence can be further explained in detail with perception-action model [25].

Definition 1.6.5. The *cognitive intelligent* robot is the agent's intelligent connection of perception to action [25].

This Brady's definition of intelligent robot focuses on the perception-action perspective. This definition is necessary for this work because this research focuses on the perception-action perspective of cognitive intelligence. However, Brady's definition does not clearly indicate *how* to achieves such intelligence. Hence, we redefined the definition of *cognitive intelligence* as below:

Definition 1.6.6. *Cognitive intelligence* is the learning ability for an agent to *guess* or *construct* the meanings of the perceived environmental information and generate its new intuition efficiently to react for ensuring its survival in the dynamic environment.

Furthermore, the cognitive intelligence definition can be further elaborated in term of *embodied cognitive intelligence* [135] in this research context as below:

Definition 1.6.7. *Embodied cognitive intelligence* is the learning ability that involves the agent's brain and its body systems (i.e. stress response system) for an agent to *guess* or *construct* the meanings of the perceived environmental information and generate its new intuition efficiently to react for ensuring its survival in the dynamic environment.

This definition explains how the cognitive intelligence is achieved and also it has the essence of perception-action perspective [25]. We also incorporate the Pfeifer's survival point of view of intelligence [135] and Oxford dictionary definition of cognition [41] and intelligence [42]. Furthermore, it is also a much shorter but detailed definition when compared to the Wall Street Journal editorial's cognitive intelligence definition [65].

We develop the diagram 1.3 to illustrate our initial understanding of intelligence. For this initial understanding model, we endorse the *biologically inspired* point-of-view in our model creation. The term biological inspired means the cross-disciplinary consideration in our models creation that emphasises more on biology and psychology discipline components. For example, biology components such as stress response system, brain regions and stress hormone and Spiking Neural Network (SNN). On the other hand, for the psychology components, examples are working memory, reference memory, cognitive control mechanisms [26] and dual-process theory [155]. However, we also consider the importance of philosophy and computational discipline components for later robot partner model implementation. In Chapter 2, we will discuss further our literature review methodology that is *synthetic modelling* [135] (definition 2.1.1) that catalysing the idea of biological inspiration of our proposed models.

Figure 1.3 shows the intelligence's components and its components relationship hierarchy. These links between two halves of intelligence are the memory, which itself splits into working memory (WM) and reference memory (RF) [10].

Based on the Figure 1.3 illustration, we assume that a higher cognitive intelligence component that interface these two memories system (working memory and reference memory) [10] together. This research describes that the higher cognitive intelligence component is the *agent's stress response system.*

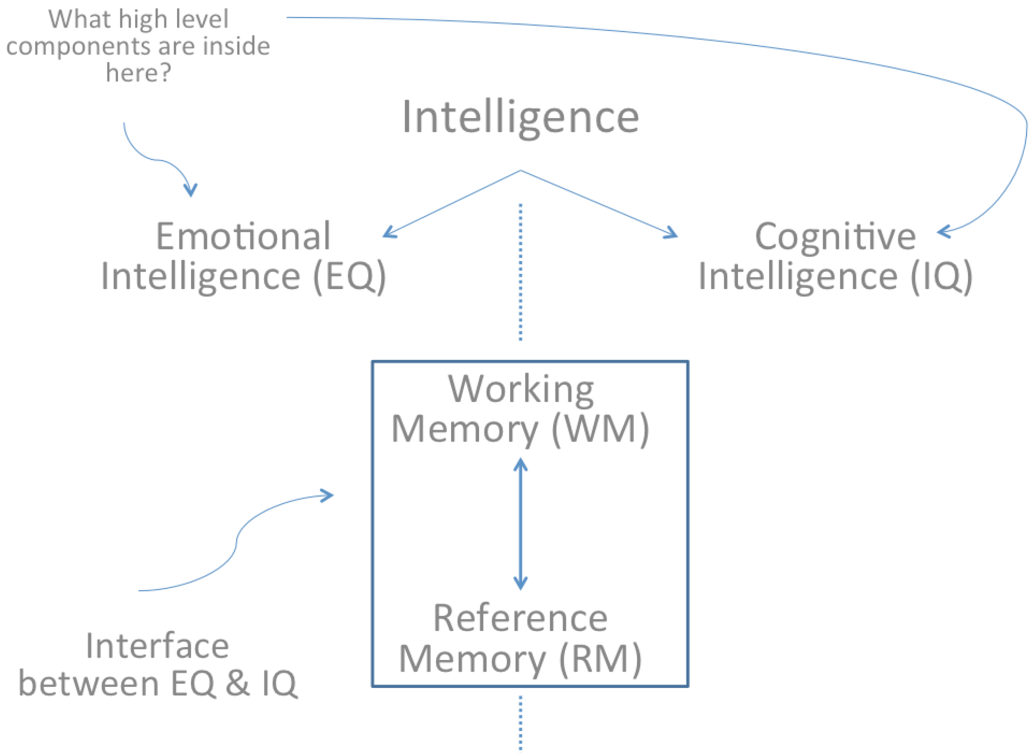


Figure 1.3: The Working and Reference Memory Interface of Embodied Cognitive Intelligence.

It is evident that emotional intelligence is related to agent's stress response system because stress itself is an emotion. Furthermore, stress hormone is correlated to working memory retrieval performance based on Lupien et al. findings [104]. On top of that, agent's cognitive intelligence is also related to working memory according to Braver et al. [26]. Hence, in this research assumption we argue that the agent's stress response system play the key roles of interfacing these memory systems and cognitive control of the agent's embodied cognitive intelligence behaviours.

1.7 Research Questions

1.7.1 Research Question 1: RQ1

What are the current problems in robot partner support for elderly people?

1.7.2 Research Question 2: RQ2

Cognitive intelligence is said to be an important factor of human intelligence. What is it exactly? And what are the state-of-the-art cognitive *models in current robot partner?*

1.7.3 Research Question 3: RQ3

Can we improve the state of the art cognitive intelligence for robot partners by applying biological principles?

1.8 Research Overview

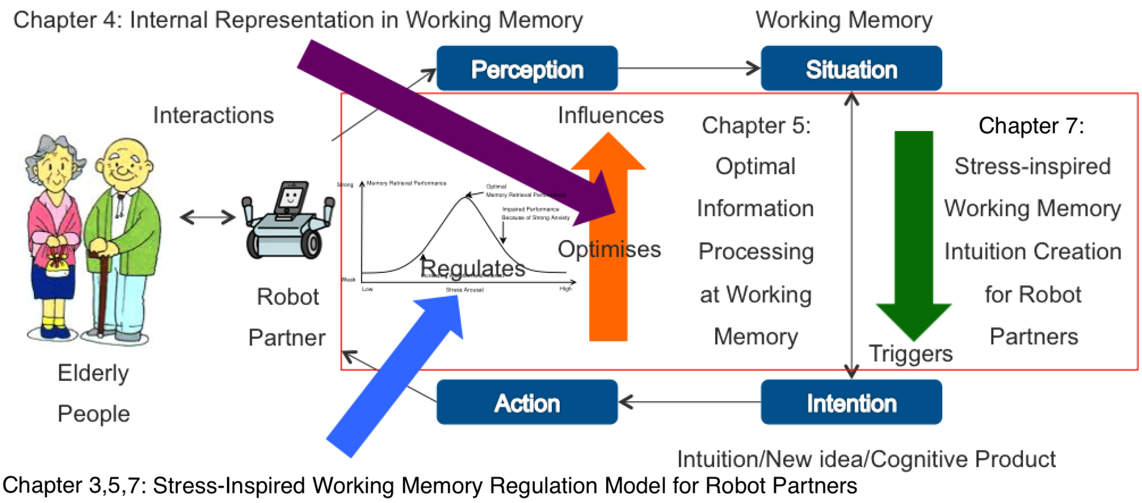


Figure 1.4: Our Research Overview for Embodied Cognitive Intelligence.

The overview of this research is focused on the red box area in Figure 1.4. The red box indicates the conditions for transitions between *situation* (or working memory) and *intention* (also known as a new idea or new intuition). The transition from working memory to a new intention is referring to knowledge generation (memory constructions) [1, 126, 127, 139]. On the other hand, intention to influence the working memory is about working memory optimisation (computation) [136]; the transitions between these two behaviours are vital concepts in modern cognitive psychology understanding [126, 127].

In recent cognitive psychology study, Braver et al. [26] had developed a working memory model that emphasise on two different control modes of cognitive intelligence: *proactive control* and *reactive control*; where proactive control focuses on working memory optimisation behaviour and reactive control describes the new intuition generation behaviour. Hence, our overall model in Figure 1.4 highlighted the modern cognitive psychology research views. Furthermore, the coloured arrows indicate the research contributions of the chapters.

In other recent cognitive intelligence research development, cognitive psychology research studies also point to the understanding of *intentionality* phenomena of transitions (or *dual mechanisms of cognitive control*) between situation and intention [77, 148]. The agent's situation (or working memory) can trigger the formation of new intention and the new intention influences (or optimises) the agent's working memory.

Definition 1.8.1. *Dual mechanisms of cognitive control* [26] are phenomena occurred during agent interchangeably uses two different cognitive control mechanisms for the working memory. First, *proactive control* is when the agent actively exhibits working memory optimisation behaviour that its intention influences its situation (or working memory); secondly, *reactive control* is when the agent passively exhibits new knowledge generation event that its situation (working memory) triggers a new intention [148]. In short, it is the two different cognitive control modes of agent's cognitive intelligence behaviours to resolve the environmental stress factors to the agent.

The focus of this research is to model the *dual mechanisms of cognitive control* (definition 1.8.1) transitions with biological stress-inspired models. In this research assumption, dual mechanisms of cognitive control are the *free will* or *improvise* behaviours because the agent can exhibit freedom to decide to improve its current understanding of the situation or create a new intuition for a better solution to mitigate the current issues in the environment. For example, a person is frustrated because he cannot find his mobile phone after he was searching for it for some time. Instead of him keeping on searching for his lost cell phone (proactive control for optimisation of his working memory with the current intention of search), he decides to improvise by using another person's mobile phone to call his phone to pinpoint his phone's location (reactive control for new idea creation). In our proposed model assumption in Chapter 6, the action to call his phone is not a previously long-term memory stored action. However, it is a newly constructed action or knowledge that is similar to his previously stored action; as an example, making a mobile phone call to locate his friend is similar to using another phone to locate his phone. As discussed in Chapter 6, the construction of the new idea is based on the memory contents that the person currently perceives (short-term memory content stored in the working memory) and the long-term memory content referenced in the working memory.

Biological stress-inspired model is an ideal model to capture these particular occurring moments of dual mechanisms of cognitive control [26]. The reason is that the agent's stress response system regulates the working memory retrieval performance according to agent's stress level. At the same time, reactive control behaviour requires a considerable amount of retrievable working memory information for construction of new intuition [49]. In other words, the agent stress response system [104] provides the timing of dual mechanisms of cognitive control transitions to occur. For instance, from proactive control to reactive control or vice versa. It is also known as agent's embodied cognitive intelligence behaviours to resolve the agent's stressful condition (the condition that needs a new solution or new intuition). In Chapter 6 and Chapter 7, we proposed the spiking reflective processing model for the dual mechanisms of cognitive control [26] in the perspective of embodied cognitive intelligence.

1.9 Research Motivations

Embodied cognitive intelligence (definition 1.6.7) research is necessary for robot partner application of social support of elderly people in ageing nations. The reason is that the elderly people acceptance of the robot partner solution depends heavily on the robot partner's embodied cognitive intelligence in this research assumption (section 1.4). As discussed in Chapter 7, the robot partner's embodied cognitive intelligence is one of the crucial factors to evaluate human-robot communication performance.

There is also the open question asked, "*If the robot partner is equipped with biological competence in embodied cognitive intelligence, will the elderly people accept the robot partner as his or her companion robot?*" It is highly motivating if such embodied cognitive intelligence can be developed in robot partner. In this thesis, there are four main identified research motivations. They are listed as follows:

1.9.1 To Improve the Existing Evolutionary Computation Operator for Effective Embodied Cognitive Intelligence Processing

The improvement of evolutionary computation optimisation performance is crucial for robot partner's embodied cognitive intelligence. The reason is that the improvement can enable better optimisation on robot partner's working memory, thus leading to a better robot partner adaptation to any new environment and ultimately survive in such environment [135] (definition 1.5.1).

Furthermore, another research outcome of this research is the improvement of evolutionary computation in fuzzy rules optimisation [167, 168]. These proposed methods are the fundamental optimisation improvement contribution. Therefore, they can be applied to different common fuzzy rules extraction problems.

1.9.2 To Develop Embodied Cognitive Intelligence Models for Robot Partner to Gain User Acceptance

As we argued in Chapter 7, the embodied cognitive intelligence in a robot partner is the key to human-robot interaction studies. Analytic system or reflective processing behaviour [151] that generates new intuition based on the raw data from the environment context information can improve conversations between the user and the robot partner during ambiguous situations in this research assumption (section 1.4).

Constant human-robot game interaction is crucial to reduce the chances of having dementia and Alzheimer's diseases for elderly people [51, 56, 181]. In this research [170] (Chapter 5), we introduced Rényi-Ulam guessing game for the robot partner social support solution to the elderly people. In Chapter 7, we improved the proposed algorithm in Chapter 5 with spiking reflective processing model [151] for human-robot interaction experiments. The robot partner is equipped with stress-inspired reflective processing on its working memory to simulate its *guessing* behaviours. We hypothesise these proposed frameworks will improve the robot partner guessing ability and thus improve the human-robot interactions.

1.9.3 To Investigate the Robot Partner's Working Memory Roles in Stress Inspired Embodied Cognitive Intelligence Model

The roles of the working memory and stress are essential for robot partner's embodied cognitive intelligence in this research context [49]. It is because stress stimulation effects are known to have influences in an agent's working memory because of high-stress hormone receptors in the human prefrontal cortex or frontal lobe [13, 104, 116] (section 2.3.4). Hence, it is ideal to investigate the relationships between stress stimulation, working memory and embodied cognitive intelligence in the perspectives of human-robot interactions.

1.9.4 To Improve the Quality of Life of Elderly People with Embodied Cognitive Intelligence Human-Robot Interactions

In this research assumption (section 1.4) the robot partner's embodied cognitive intelligence can improve human-robot interaction between the robot partner and the elderly people [51, 56, 181]. The research assumption (section 1.4) motivates us to investigate biological competent embodied cognitive intelligence to reduce the rejection rate of the robot partner solution.

Embodied cognitive intelligence for human-robot conversation is essential in robot partner solution [51, 56, 181]. In this research [169], the proposed robot partner embodied cognitive intelligence model is enhanced with working memory and stress models. Then the model is experimented with human-robot conversation in natural data environment setting. Hence, the natural environment settings provide natural data input for the robot partner. The reason is natural data learning is crucial for agent's cognitive learning according to Wagman et al. [180] and Neisser [126, 127].

1.10 Research Objective

The objective is to investigate biological stress inspired models that able to produce artificial humanlike embodied cognitive intelligence conversation behaviours for robot partner. The simulated embodied cognitive intelligence conversation behaviours in Chapter 7 are then experimented to gain user acceptance, user engagement and positive emotional and social attitude change towards robot partner.

As a result, to achieve this research objective, we discuss the multidisciplinary point of view of robot partner's embodied cognitive intelligence in Chapter 2's literature review. It is because a deep analysis of the relationships and gaps that exist in biology, psychology, philosophy and computational research literature can comprehend the current issues with existing models of embodied cognitive intelligence. Embodied cognitive intelligence for robot partner is a very challenging and broad research field. Thus, our proposed robot partner's embodied cognitive intelligence overall development is divided into smaller chapters according to the research overview section (Figure 1.4).

1.11 Research Hypothesis

If a robot partner is equipped with the proposed spiking reflective processing model (Chapter 7), then its working memory and its stress inspired models can deal cognitively with the uncertain surroundings with new intuition and working memory dynamic optimisation to mitigate its environmental issues. Consequently, the robot partner is said to be a better support in non-stationary surroundings that its user inhabit. Therefore, the robot partner can socially assist its user in term of emotional, social interaction and social perception positive attitude change towards the robot partner.

1.12 Chapter Summary

In this first chapter, problems of the ageing society and the robot partner solution are introduced. We also listed the needs of ageing society and the importance of robot partner in an ageing nation. For example, evidence of substantial government support is given to emphasise the significant of robot partner solution to the ageing society.

The focus of this chapter is the understanding of the notion of agent's intelligence. Many aspects of intelligence are being investigated such as research history of intelligence, components of intelligence, definitions of intelligence, different categories of intelligence. Then, we defined the term embodied cognitive intelligence (definition 1.6.7) as our prime perspective of agent's intelligence in this research. We draughted our initial understanding of agent's embodied cognitive intelligence model that interfaces both working and reference memories system.

Furthermore, we explain our focus on embodied cognitive intelligence in term of agent's stress response system and working memory integration. Next, we emphasise the importance of dual mechanisms of cognitive control [26] (definition 1.8.1) in agent's working memory processing and its relations to stress response system. We support the Braver's view of dual mechanisms of cognitive control as the essence of embodied cognitive intelligence processes in agent's working memory [26].

Then, the research questions and the research motivation are defined. An overview of this research is also discussed. In the next chapter, a comprehensive literature review will investigate the state-of-the-art embodied cognitive intelligence literature in four different research discipline areas, we will investigate these research discipline areas with the focus on agent's working memory and stress response system.

Table 1.1: The History of Cognitive Intelligence Research [59, 123]

Year	Author	Descriptions
1832-1920 AD	Wilhelm Wundt	He established the first psychology laboratory for research at the University of Leipzig. He emphasized the notion of introspection. It is a method of examining the inner feelings of an individual. He focused on three areas of human's mental functions that they are images, thoughts and feelings. These mental functions are the foundation areas studied today in the cognitive psychology field. Many of the perceptual processes studies can be traced back to his work [123].
1850-1909 AD	Hermann Ebbinghaus	He attempted to apply mathematics to mental representations; he used precise quantitative methods to investigate human memory capabilities [123].
1863-1930 AD	Mary Whiton Calkins	She was an American pioneer female in the field of psychology. Her work focused on the human's memory capacity. She introduced a theory called the recency effect. This theory explains the tendency of an individual to be able to recollect accurately memory on the most recent item that presented to the individual [123] is higher.
1842-1910 AD	William James	He focused on the human learning experience in everyday life and its importance to the study of cognition. His main contribution was his textbook "Principles of Psychology" that examines many components of cognitive intelligence [78].
1928-2012 AD	Ulric Gustav Neisser	He is also known as the "father of cognitive psychology". He argued that most of the psychology experimental settings ignore the real world environment but in favor of the laboratory's settings. Furthermore, he claimed that human's memories are mostly reconstructed (knowledge or new intuition generation) and not just an accurate snapshot of a particular moment [126, 127].

Chapter 2

Literature Review

2.1 Chapter Introduction

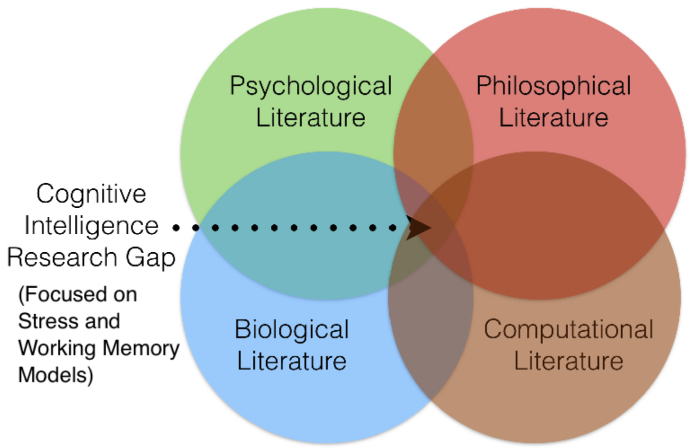


Figure 2.1: Synthetic Modelling Approach [135] for Identifying Cognitive Intelligence Research Gap in the Cross Sections of the Four Main Research Discipline Areas.

This chapter is a multidisciplinary literature study that focuses on four research discipline areas related to cognitive intelligence that are *biology, psychology, philosophy* and *computational* areas (Figure 2.1). This research defines the cognitive intelligence research gaps as located in the cross sections of the four main identified research discipline areas (section 2.2). Although these four research discipline areas have examined many different parts of cognitive intelligence research, there has not been any research that rigorously investigates into the *stress* and *working memory* perspectives for robot partner's embodied cognitive intelligence.

Hence, this literature study introduces an additional insight into the stress and working memory perspectives for robot partner embodied cognitive intelligence with cross sections consideration of these four research discipline areas. In later chapters, the identified embodied cognitive intelligence (working memory and stress) model via synthetic modelling [135] (section 2.2) of this literature review will be implemented in robot partner agent, the identified embodied cognitive intelligence model is needed to improve the human-robot interactions as explained in section 1.4. Synthetic modelling is a modelling methodology to understand intelligence by building artificial system [135] (definition 2.1.1). Hence, the analytic focus on robot partner application for elderly people support so it can successfully address the elderly's social needs.

Definition 2.1.1. *Synthetic modelling* is a model building methodology to understand intelligence. The synthetic model is the intersected areas between empirical sciences that follow an analytic approach (i.e. biology and psychology) and synthetic approaches (i.e. philosophy and computer science) [135].

Although numerous studies [103, 104, 105, 106] have identified stress and working memory in dual mechanisms of cognitive control [26] and its relationship to embodied cognitive intelligence, little analytic attention has been paid to the stress and working memory perspectives of embodied cognitive intelligence for human-robot interaction. This research addresses this issue by demonstrating the stress and working memory model effectiveness for simulating dual mechanisms of cognitive control [26] (section 1.8.1) of the robot partner for its embodied cognitive intelligence behaviour in human-robot conversational interactions.

The research question 3, RQ3 (subsection 1.7.3) will be answered in the following sections with multidisciplinary perspective considerations.

2.2 Defining Embodied Cognitive Intelligence Research Gap

In Shaw's work [148], *intentionality* is an important ecological idea that resides on these three concepts, *process*, *act* and *experience*. The process belongs to the physics domain; the act refers to the biology domain, and experience belongs to the psychology domain. As in this research, a multidisciplinary understanding of embodied cognitive intelligence point of view is also emphasised in Shaw's work [148]. However, the specific effects of *experience* on the *act* and their relationship to the *process* are not investigated in Shaw's work [148]. For example, the impact of stress hormone (biology) towards the memory retrieval performance (psychology) is an inverted-U-shape relationship as indicated by Lupien et al. [104].

Therefore, we define embodied cognitive intelligence research gap as the common terminologies intersected between four different disciplines that are biology, psychology, philosophy and computation research areas. The *synthetic modelling* [135] (definition 2.1.1) is the process of identification of the intersected terminologies across different cognitive intelligence research disciplinary. The synthetic modelling also refers to the creation of an artificial system that simulates certain parts of a natural system [135].

The *synthetic modelling* approach focuses the importance of the understanding of intelligence by building natural system [135]. For instance, by building an agent with artificial behaviours, we can study the agent's cognitive intelligence with the observation of its interaction behaviours with the environment. Therefore, we are draughting our cognitive intelligence model with the synthetic modelling approach. Then we evaluate our models by building artificial agents (robot partners) to observe its human-robot interaction's cognitive behaviours in the following chapters.

The identified common intersected terminologies that existed in these four research areas are the *working memory* and *stress* models [26, 104]. We argue that agent's stress response system can modify the operation of working memory and it will effects both IQ and EQ of the agent. For example, agent's working memory (psychology) is related to stress (biology) as indicated by Lupien et al. [104] and working memory (psychology) is correlated with cognitive control process (computation) [26]. Furthermore, working memory (psychology) is related to scaffolding mind theory (philosophy) [34]. Therefore, working memory and stress models are the common terminologies of cognitive intelligence.

2.3 Biological Systems: Literature Review

In a human body, many different biological systems that support the body's survival. However, one particular important biological system that is the *stress response system* (subsection 2.3.1), it ensures the survival of the human. Pfeifer's definition of cognitive intelligence (definition 1.5.1) is *the ability to survive* [135]. Consequently, the biological stress response system is selected from other systems because *stress is related to survival.* The stress response system also has a direct relationship with cognitive intelligence behaviour according to Yerkes and Dodson law on stress [186].

The stress response system (subsection 2.3.1) is also known to have a strongly correlated relationship with human working memory retrieval performance according to Lupien et al. [104]. The working memory is one of the important parts of human embodied cognitive intelligence [106]. For example, during a middle-stress condition, the human's embodied cognitive intelligence will perform optimally [186]. On top of that, optimal cognitive intelligence performance condition will lead to the reactive control [26] mechanism for new intuition creation behaviours. Hence, it is trivial to establish the relationship between the biological stress models and its working memory retrieval performance to investigate the human's embodied cognitive intelligence. Thus, stress response system is selected out of other biological systems in the human body for the understanding of human embodied cognitive intelligence.

2.3.1 Hypothalamic-Pituitary-Adrenal (HPA) Axis Stress Response System

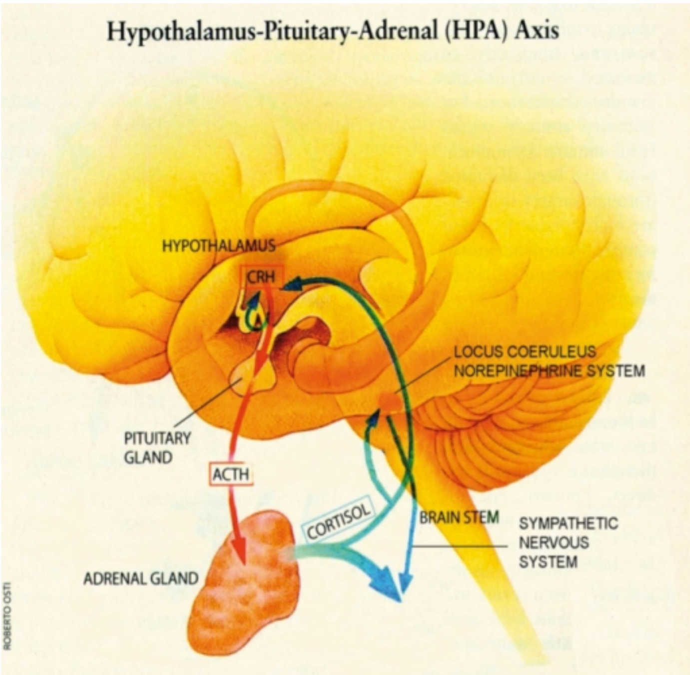


Figure 2.2: The hypothalamic-pituitary-adrenal (HPA) Axis for Human's Stress Response System [131, 133]. *We obtained the permission to reuse the copyrighted figure from Roberto Osti. ©Roberto Osti.*

Figure 2.2 describes the hypothalamic-pituitary-adrenal (HPA) axis [133] for a human's biological stress response system. Firstly, stressors from the environment received by the human's sensory input such as eyes, ears, touch, smell and hear are interpreted by the human brain and then the interpretation will lead to a reaction by the hypothalamus. Subsequently, the hypothalamus will initiate the secretion of peptide corticotropin-releasing hormone (CRH) into the blood stream. CRH will then travel in the bloodstream and reach the anterior pituitary gland to trigger further the peptide adrenocorticotropic hormone (ACTH) secretion into the bloodstream for the targeted organ of adrenal glands. The fasciculata layer in the adrenal gland will react to ACTH and thus produce the *cortisol steroid hormone (stress hormone)* via steroidogenesis process [137].

Cortisol steroid hormone, the stress hormone, will affect the metabolic system. For example, an individual with high-stress hormone will experience a higher blood pressure, higher blood glucose level and higher heart beat. The reason that stress hormone causes these physiological changes are to enable the agent to escape from danger and to survive. For example, additional blood glucose level and higher heart beat rate are needed to generate extra stamina to escape from danger.

The *excitatory* effect is the continuous stress stimulation from the environment that increases the stress hormone in the human body. On the other hand, the successful danger avoidance behaviours that reduce the stress stimulation from the environment are known as *inhibitory* effects. The inhibitory effect signals the anterior pituitary and hypothalamus to suppress CRH and ACTH secretion [137]. Thus, the suppressed CRH and ACTH secretion will lower the overall stress hormone level in the bloodstream.

The human's stress response system is a steroidogenesis system [137]; it requires some time interval for the stress hormone production and its travel from one gland to another through the bloodstream in the HPA axis (Figure 2.2). Thus, this steroidogenesis phenomenon is important to understand that the human's cognitive intelligence is also regulated according to the steroidogenesis system's temporal-delayed behaviours. For instance, it takes time for the stress hormone to be generated and reach prefrontal cortex (the brain area that responsible for working memory and it has high-stress hormone receptors) to alter the working memory retrieval performance.

2.3.2 Hippocampus

The curved elongated ridge is the hippocampus (Figure 2.3) that is a part of the brain that connected to amygdala (subsection 2.3.3). Furthermore, the hippocampus is the brain area that is known to have a high number of glucocorticoid (stress hormone) receptors and is known to have an effect on reference memory [10] and learning [37, 105, 106, 115, 116].

The hippocampus is known to be involved in forming, storing, and processing reference memory (subsubsection 2.4.5) [120]. Specifically, the hippocampus provides features such as contextual information and episodic (subsubsection 2.4.5.1) memory.

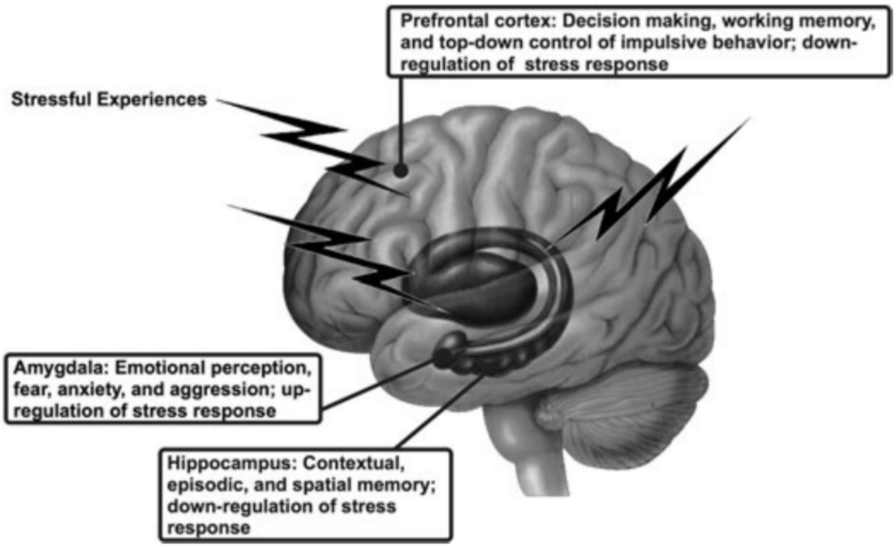


Figure 2.3: Illustration of the Main Stress Components in the Human Brain and Its Activities and Effects [116]. *We obtained the permission to reuse the copyrighted diagram from John Wiley and Sons. ©John Wiley and Sons.*

The hippocampus also has the functionality for down-regulation of stress response system [116] (Figure 2.3). Down-regulation of stress response system refers to the inhibitory effects to reduce stress hormone level in the body.

The hippocampus under the stress hormone regulates the formation of new reference memories [10] (subsubsection 2.4.5) such as semantic memory (subsubsection 2.4.6) and episodic memory (subsubsection 2.4.5.1). The formation of new memory [126, 127] is also referred as the *formation of new intuition* for the agent. The agent's working memory stores both reference memory as well as currently detected concepts from the environment (Figure 1.3). In Chapter 6 we will discuss the new intuition construction is consisting of the combination of long-term memory content and short-term memory content in the working memory. Thus, it leads to the interesting assumption in this research that the hippocampus, stress and reference memory are related systems in embodied cognitive intelligence in the processing, storing and forming of new reference memory (new intuition).

2.3.3 Amygdala

The *amygdala* (Figure 2.3) is an almond-shaped mass located in the centre of the brain [118] that next to hippocampus (subsection 2.3.2). The amygdala has high glucocorticoid (stress hormone) receptors, fear processing, aggression behaviours, anxiety processing and memory for emotionally relevant information also known as flashbulb and traumatic memory (subsubsection 2.4.5.3) [104, 115, 116]. It also functions in up-regulation of stress response system [116] (Figure 2.3).

In the point of view of cognitive psychology, the amygdala can be considered as the brain's memory organ that stores the emotion memories such as flashbulb and traumatic memories (subsubsection 2.4.5.3). The amygdala's emotion memories function is essential to the agent's overall survival (definition 1.5.1). The reason is that it can trigger early warning (stress hormone) to the agent about any events or objects that are threatening to the agent's survival. Ironically, cognitive intelligence and survival are related according to Pfeifer's [135] cognitive intelligence definition 1.5.1.

Flashbulb and traumatic memories are adaptive to different agents because these memories can associate any concepts with emotions during the agent's encounter with a significant event. The memory system is adaptable to different living contexts of the agent that are only significant to that particular agent (example 2.3.1). In other words, the formation of flashbulb and traumatic memories is unique to individual agents. In Chapter 3, flashbulb and traumatic memories are tested with extreme stress stimuli for the robot partner to find the optimal path to the designated goal. In Chapter 6, we used the agent's previous life experiences as the stress stimuli for our experiment design. Different agents have their traumatic memories. Therefore, the life experiences questionnaire [144] is intended to ask the most frequent questions that could activate their traumatic memories to stimulate stress emotion for the experiment.

Example 2.3.1. To illustrate an example of flashbulb memory is peculiar to an agent. An agent X who works in the jungle as a ranger is sensitive to noises or movements produced by a wild predator such as the tiger. On another hand, an agent Y who works in a chemical factory is sensitive to chemical smells. To further illustrate this example, the agent X may not be sensitive to smell as the agent Y may not be susceptible to predator noise or movements.

2.3.4 Prefrontal Cortex (Frontal Lobe)

The *prefrontal cortex* (Figure 2.3) is the brain area located behind the forehead [119]. Human's prefrontal cortex has been discovered to be involved in emotional processing [13]. It is also known to have high glucocorticoid (stress hormone) receptors and working memory processing [13, 26, 104, 116].

The working memory (subsubsection 2.4.4) is the essential components of cognitive control mechanism [26] that allows a small amount of information to be available for a limited period [8]. The prefrontal cortex is also known to have the effect of top-down control of impulsive behaviours and down-regulation of stress response system [116] (Figure 2.3).

The prefrontal cortex or the frontal lobe is the brain area that holds and processes the working memory. It is also the brain area involved in analytical thinking and planning [116]. In the cognitive intelligence point of view, Braver [26] proposed the dual mechanism of cognitive control mechanism (definition 1.8.1) that explains the cognitive processing behaviour in the agent's working memory. Hence, it inspired us to suggest that the prefrontal cortex reassembles the area for evolutionary computation optimisation (subsection 2.6.6) of robot partner's working memory. The reason is that Braver [26] argue that prefrontal cortex is the brain area that does both cognitive control process and storing of working memory in his proposed model.

Furthermore, evolutionary computation optimisation methods have been used to optimise robot partner's path planning [24]. Therefore, evolutionary computation optimisation is a suitable computation method for agent planning and processing.

In Chapter 5 and Chapter 7, the robot partner's working memory is optimised by evolutionary computation proposals proposed in this research. On top of that, this research also discusses the improvements of optimisation algorithm operators in Chapter 4.

2.4 Psychological Models: Literature Review

In this section, we discuss the psychological models of embodied cognitive intelligence. Psychological models refer to the stress perspective of psychological concepts and empirical study of mind on an agent. According to definition 1.6.7, embodied cognitive intelligence is the learning ability that involves the agent's brain and its body systems (i.e. stress response system) for an agent to *guess* or *construct* the meanings of the perceived environmental information and generate its new intuition efficiently to react for ensuring its survival. Hence, psychological stress plays an important part to measure the environment's stress effects on the robot partner. It is to enable the robot partner to know when to trigger the heuristic [149] (subsection 2.4.7) behaviour (formation of new intuition) to solve the problems in the environment.

The nature of stressor stimuli can be categorised into two different stress categories, i.e. absolute stress and relative stress. Then, this section also explains the relationship of stress response system, working memory and embodied cognitive intelligence behaviours for an agent. Next, we explain the heuristic technique [149] (subsection 2.4.7) about agent's new intuition creation behaviour. In summary, this section explains the psychological point of view on the agent's embodied cognitive intelligence.

2.4.1 Absolute Stress

Definition 2.4.1. *Absolute stress* is a feeling of a person when he or she is confronted with real danger from the physical environment introduced [104].

Absolute stress is the extreme stress stimuli with fear of physical pain involved that potentially cause injuries or death to the agent. For example, absolute stress is experienced when a person is confronted with a forest fire, car accident, tsunami or earthquake.

In another point of view, on the concept of absolute stress, the determinants of the stress response are non-specific [146]. In other words, unspecific conditions can put a strain on the agent and lead to disease, in the same way that the constant unspecific conditions can put a strain on a piece of an object and break it [104]. In short, absolute stress reassembled the signals to the agent about the severe environment threat to its survival.

In this research, absolute stress is the extreme stress simulation conditions for the robot partner. However, these conditions are not the goal of this research because this research focused on the embodied cognitive intelligence improvements for human-robot interactions. Furthermore, in Yerkes and Dodson [186]'s stress curve perspective, absolute stress will increase the stress arousal axis to the maximum, while optimal embodied cognitive intelligence is only in middle-stress condition. Therefore, absolute stress condition impairs embodied cognitive intelligence performance and thus is not actively discussed in this research.

In contrast, for the robot partner's survival, absolute stress is a necessary condition for the robot partner to remove itself from the danger from the environment. In Chapter 3, absolute stress stimuli are tested for the robot partner to find an optimal path to the designed goal.

2.4.2 Relative Stress

Mason [111] described three main psychological determinants that would lead to relative stress reactions in any individual who is exposed to them. In addition to that, Lupien et al. [105] divided relative stress into four main categories with additional social evaluative threats, i.e.

1. *Novel*: a new concept or percept detected. For example, a new object concept is detected that is not available in the robot partner's long-term memory.

2. *Unpredictable*: an incident that suddenly happens. For example, sudden changes in the room lighting conditions.

3. *Uncontrollable*: a situation that cannot be amended. For example, a player is going to lose a game and cannot do anything about it.

4. *Social*: a threat interpreted by the social community as an unpleasant situation. For example, a person says that man is very abusive.

Relative stress is focused in this research rather than absolute stress. The reason is relative stress is more suitable for human-robot conversation. For example, in novelty-triggered relative stress, when a new conversation topic is spurred in a human-robot interaction between the robot partner and the elderly person, the robot partner needs to enable its embodied cognitive intelligence to guess the meaning of the new conversation topic and react to it accordingly.

Nevertheless, absolute stress topic is also discussed in the simulated robot partner experiment in Chapter 3. The absolute stress-stimulated is tested on high-stress stimuli for the robot partner to find the optimal path to the targeted goal. In Chapter 3, relative stress is also simulated as a stressor for the robot partner at the same time. We also utilise previous life experiences survey [144] as relative stress stimuli to validate our proposed model in Chapter 6.

Example 2.4.1. Simon et al. have proposed the gin and tonic test [43] that has similar characteristics of a relative stress test on robot partners. The gin and tonic test is a test on a robot partner bartender named Jimmy that produces multiple drinks to a consumer. However when a consumer requests multiple drinks but does not consume any of the drinks for multiple numbers of times for some unknown reasons (*novel*, *unpredictable*), the Jimmy robot partner should react cognitively to *understand* or *guess* the consumer's situation and follow by appropriate action to resolve the consumer's issues. The feature of *guessing* in relative stress test was defined in the previous chapter as the basis of cognitive intelligence as definition 1.6.6 and definition 1.6.7. In certain conditions, the consumer's issues may not be resolved (*uncontrollable*) if the consumer does not want to communicate with the robot partner. In the (*social*) point of view, the social information may trigger relative stress in the robot partner; information that indicates the consumer is in some depressed situation. In summary, Simon et al.'s gin and tonic test [43] reassembles many similarities of a relative stress test for a robot partner.

2.4.3 Yerkes and Dodson Stress Curve Model

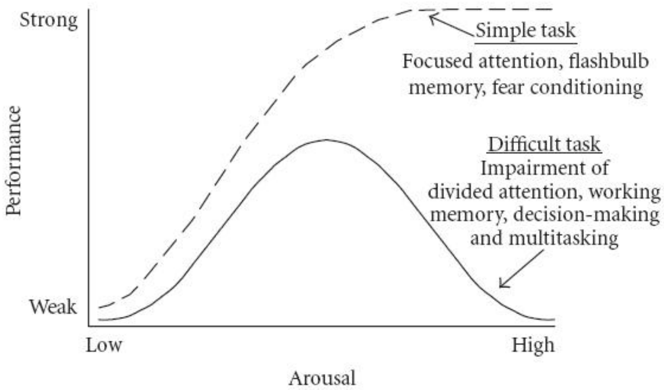


Figure 2.4: Yerkes and Dodson Stress Law Graph on Stress Arousal against Cognitive Intelligence. *Copyright ©2007 David M. Diamond et al. [40]. This figure is from an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.*

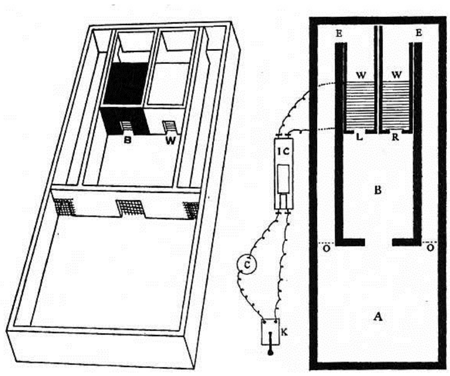


Figure 2.5: Illustration of the Yerkes and Dodson Experiment with Mice Maze [186]. *The permission to reuse the copyrighted diagram was obtained from John Wiley and Sons. ©John Wiley and Sons.*

Yerkes and Dodson were the pioneer researchers who discovered the stress inverted-U-shape graph phenomenon (Figure 2.4), which is the Gaussian-like relationship between stress arousal and cognitive intelligence of mice [186]. Figure 2.5 shows the first Yerkes and Dodson experiment with mice in a maze for stress test [186]. The experiment was based on visual discrimination embodied cognitive intelligence test for mice with the white and black coloured entrance boxes. The black and white coloured entrance boxes were designed to be interchangeable. Occasionally the black and white boxes were swapped with their locations. A black coloured box would get an electric shock as a penalty when the mice passed through it. Eventually, the mice will learn to associate the black coloured entrance box with a penalty at the end of the experiment and thus, their behaviours during the experiment were recorded. Multiple rodents were tested to produce the inverted-U-shape graph experiment outcome.

Hence, the Yerkes and Dodson [186] established the multidisciplinary research link between stress and cognitive intelligence and thus formed the study of stress-based embodied cognitive intelligence (definition 1.6.7). The discovery of Yerkes and Dodson stress inverted-U-shape graph phenomenon [186] is a significant contribution to embodied cognitive intelligence research field. The Yerkes and Dodson discovery established the first multidisciplinary research link between biological stress and cognitive intelligence that was previously separated research fields.

On top of that, the timing of when the heuristic behaviour [149] (subsection 2.4.7) should have more probability to be triggered by middle-stress conditions can be estimated with the Yerkes and Dodson stress inverted-U-shape graph. In a recent research, Lupien et al.'s [104] discovery of the stress relationship with working memory retrieval performance was also based on Yerkes and Dodson's [186] initial discovery.

Therefore, Yerkes and Dodson [186] and Lupien et al. [104] inspired this research to model the robot partner's embodied cognitive intelligence with stress inspired models to improve the human-robot interactions. The reason is these [104, 186] discoveries that middle-stress level exhibits full potential of agent's embodied cognitive intelligence. Hence in Chapter 7, we want to harvest this full potential of embodied cognitive intelligence to robot partner human-robot interactions behaviour.

2.4.4 Volatile or Short-term or Working Memory

Honig [75] initially discovered the concept of working memory. Further enhancement of the working memory model was proposed by Alan Baddeley and Graham Hitch [7]. Working memory's contents has limited time duration for its availability in the human's memory. Furthermore, working memory is also very fragile where it can be lost or updated with distraction or passage of time. Another term used to describe the concept of human's working memory is a short-term memory.

The Miller's magical number 7 [121] is the research study on human working memory capacity. In his work, the magical number 7 is referring to the working memory that has an average capacity to store 7 ± 2 concepts. However, according to

Cowan [38] human has the working memory capacity that can extend to more than 7 ± 2 concepts. Therefore, in this research assumption the robot partner's working memory capacity can be extended up to 7×7 concepts based on different stress arousal level as indicated by Lupien et al. [104].

Another important property of working memory is that it is primarily acoustic where memories are stored in the sound code [100, 121, 122]. In Chapters 5 and 7, the content stored in robot partner's working memory is in word strings format. Word strings format is needed to substitute acoustic based content [100] because of robot partner's working memory optimisation requirement in Chapter 5.

Definition 2.4.2. *Working memory* is the memory processing system that is responsible for repetitively holding various instances of temporal information in the mind, where such memory are continuously processed [14].

Working memory is an important embodied cognitive intelligence concept in this research. The reason is that human's embodied cognitive intelligence performance will change based on different stress arousal conditions [104]. Working memory is also highly correlated to cognitive intelligence according to Braver et al. [26]. Furthermore, Braver et al. [26] proposed dual mechanisms of cognitive control for explaining the cognitive intelligence processing on working memory [26] (definition 1.8.1). Therefore, we selected and focused the robot partner's working memory and stress response system; the reason is that both of them have empirical evidence to support their relationship to human's embodied cognitive intelligence.

In an event of retrieving the working memory during the robot partner's middle-stress condition, the reference memory concepts referenced by recent perceived concepts can be temporarily stored in the robot partner's working memory. The reason is due to more efficient working memory retrieval performance (larger working memory capacity) [104]. Example 2.4.2 explains these phenomena clearly. Consequently, the robot partner stores two different types of memories in its working memory, i.e. the reference memory concepts and currently perceived memory concepts. The amount of memory concepts that can be stored in the working memory is conditioned by the robot partner's stress arousal status and Miller's conditions [104, 121]. As discussed earlier, the working memory capacity can be extended according to Cowan [38].

The working memory is also the memory fragment stored that temporarily registers concepts in the environment as what the robot partner encounters. In this research assumption, working memory is the clues and parts for constructing the new idea when heuristic behaviour conditions are met. In Chapter 7, we discussed the heuristic behaviour [149] (subsection 2.4.7) conditions. Hence, the new idea content is also limited by the concepts stored in the working memory as perceived by the robot partner at the particular moment. In other words, the robot partner's new intuition creation process is viewed as new intention construction with robot partner's working memory contents.

Example 2.4.2. On the occasion when a person sees an umbrella, then the umbrella concept is stored temporarily in the person's working memory. Next, the umbrella reminds him of taking his water bottle before going outdoors. The umbrella is ontologically linked to water and outdoors. Therefore, the water and outdoors concept are the reference memory temporary loaded into the person working memory when he sees an umbrella. Outdoors and water (in the working memory) are the part of the constructed new intuition or cognitive product. In this example, the person's new intuition is "taking his water bottle before going outdoors".

2.4.5 Declarative or Reference Memory

Definition 2.4.3. *Declarative memory* or *reference memory* refers to memories that can be consciously recalled such as facts and knowledge [10, 178].

Declarative memory [178] (also known as reference memory [10]) is a type of long-term human memory system. Reference memory has two subcategories, episodic memory (subsubsection 2.4.5.1) and semantic memory (subsubsection 2.4.5.2). Furthermore, declarative or reference memory can be accurately stored and retrieved in an extended period. For an example of reference memory such as home address, telephone number, birthday dates and names. Reference memory is useful for robot partner during its human-robot communication session, the reason is reference memory can be utilised to store its user's profile information to facilitate its conversation with its user. The reference memory also exists in the form of emotional life events memories for the agent [144]. After the agent is stimulated with stress stimuli, the reference memory can load into the agent's working memory as long-term memory content [85].

The robot partner's reference memory and its relationship with working memory are viewed as the proactive control [26] mechanism interface. Figure 1.3 illustrates our understanding of reference memory. In Chapter 5 and Chapter 7, the robot partner's reference memory will load into the working memory during its proactive control [26] mechanism where robot partner optimises its working memory towards its intention. The robot partner's artificial stress response system acts as the regulator to control its working memory retrieval performance. Hence, its stress response system control the total amount of reference memory to be loaded into its working memory in different stress condition.

2.4.5.1 Episodic Memory

Definition 2.4.4. Tulving's *episodic memory* definition refers to storage and retrieval of spatially situated, temporally dated, and in-person experiences, and temporal-spatial relations of events [173, 174].

Definition 2.4.5. Schacter's *episodic memory* definition is the memory of life events that can be expressively stated such as associated emotional feelings, locations, dates, and contextual information [145].

The episodic memory (definitions 2.4.4 and 2.4.5) described as a long-term memory type system that stores the spatial-temporal associated memory for an agent. For an example of episodic memory, the pathway for going back home, where to find a book on the bookshelf and events happened on the wedding day. The episodic memory is necessary for the spatial-temporal related problem of an agent such as optimal path search.

The Chapter 3 simulated agent's episodic memory is stored as Markov Decision Process (MDP) model in table matrix data structure. The Markov Decision Process (MDP) model is utilised for path optimisation to its designated goal. In Chapter 3, we will discuss the simulated agent's episodic memory and the integration of artificial stress response system. The simulated agent will converge its optimal path solution with reinforcement learning approach in the MDP model. The reason we choose MDP problem to explain the concept of episodic memory because both of them involve spatial and temporal related memory feature.

2.4.5.2 Semantic Memory

Definition 2.4.6. *Semantic memory* is the memory involved with storage and use of knowledge about words and concepts, their properties, and interrelations [173, 174].

Semantic memory (definition 2.4.6) is a type of agent's long-term memory system that facilitates its storage and retrieval of concepts and words and their interrelations. For example, when an agent sees any types of a building and then the agent can recognise it as a condominium. The semantic memory system is related to agent's concept detection such as image concept detection and speech recognition.

In Chapters 5 semantic memory is discussed as robot partner's image concept detection model [147]. The deep learning neural network model is trained with a high volume of training samples and acts as the semantic memory for the robot partner. Next, in Chapter 7, the image concept detection model is improved with image search engine [80, 81] for object's label detection that acts as the semantic memory behaviour for the agent.

Furthermore, the interrelations of semantic concepts are discussed in Chapters 5 and 7 with the OpenCyc human expert semantic ontology system [98]. The robot partner's heuristic behaviour also involves inferences of related semantic concept in Example 2.4.2.

2.4.5.3 Flashbulb and Traumatic Memories

Definition 2.4.7. *Flashbulb memory* is the memory that captures a highly detailed, extraordinary vivid *snapshot* of the moment triggered by an event that is surprising and consequential (or emotionally arousing) [27].

Flashbulb and traumatic memories (definition 2.4.7) are the products of absolute stresses after extreme stress stimulation conditions. This memory type is stored as the association of concepts and the strong stress emotion attribute in a form of agent's long-term memory. For example, when a dog bites a person, the person will associate strong stress emotion to the dog concepts as his or her long-term memory.

In Chapter 3, the simulated agent learns the flashbulb and traumatic memories from the neural network training with extreme stress stimuli in the virtual environment. The simulated agent will raise its stress level when it detected its obstacles that are previously associated with flashbulb memory (strong stress emotion associated memory). Hence, the simulated agent's stress response system is will enable wider working memory retrieval performance [104] for a better solution to mitigate the situation.

2.4.6 Working Memory Retrieval Performance Model

In early neuropsychology research, initial studies have established the relationship between agent's glucocorticoid (stress hormone) and its embodied cognitive intelligence behaviours. For example, on the effects of glucocorticoids on human working memory retrieval performance. A dose-response study showed that the impact of hydrocortisone on human working memory retrieval performance depends upon the dose introduced to the subjects [15]. Hence, the relationship between agent's stress

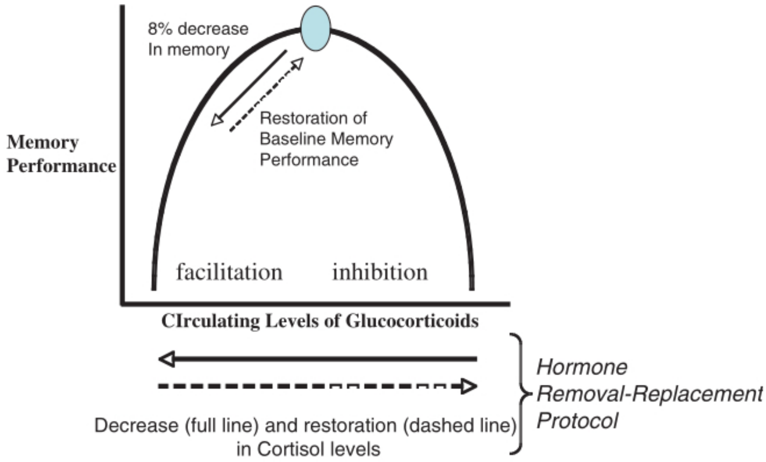


Figure 2.6: Schematic Representation of the Modulation of Working Memory Performance Versus Circulating Levels of Glucocorticoids [104]. *The permission to reuse the copyrighted diagram was obtained from Elsevier. ©Elsevier.*

response system, working memory and embodied cognitive intelligence are the well-established research field in cognitive psychology because many early work can be traced back to 20th-century research [15, 186].

In recent related cognitive psychology research work, Lupien et al. [106] tested young male subjects for working memory on a list of 12 words with different doses of glucocorticoids (cortisol or stress hormone). A graph of working memory retrieval performance against the level of glucocorticoids also exhibits the inverted-U-shape phenomenon (Figure 2.6), as early described by Yerkes and Dodson [186]. Lupien et al. [106]'s work is an important multidisciplinary link that indicates human's stress hormone is directly related to working memory. Furthermore, human's working memory is directly related to embodied cognitive intelligence according to Baar [5] and Braver et al. [26]. Hence, human stress response system and embodied cognitive intelligence are directly related systems. These systems corporate with each other to derive human intelligence to survive in his or her environment [135] (definition 1.5.1).

Thus, Lupien et al. [106] discovery inspires this research to focus on human's working memory retrieval performance and its relationship to stress response system as robot partner's embodied cognitive intelligence behaviour.

2.4.7 Heuristic Technique

The term *heuristic* refers to "discover" or "find" in Greek. Herbert [149] discovered the concept of heuristic technique. However, much of the work of discovering heuristics in human decision-making was conducted by Amos Tversky and Daniel Kahneman [176]. The heuristic technique is a problem-solving technique that follows a reasonable methodology that is not optimal, but adequate for one's immediate intention goals [134]. Although the condition where heuristic technique is applied when finding an optimal solution to a problem is intractable or difficult, the heuristic technique is potentially useful to increase the speed of finding a sufficient immediate settlement to a complex problem. In other words, heuristic techniques are the psychological shortcuts that reduce the *cognitive load* [165] (subsubsection 2.4.7.2) of deriving a decision during agent's reactive control mechanism [26] (definition 1.8.1). Examples of heuristic techniques are the use of the rule of thumb, trial and error, an educated guess, an intuitive judgement, the best guess or common sense. Likewise, heuristic techniques are the tactics that use promptly available, but loosely related information to manage the problem-solving mechanism in human beings and as well as robot partners.

From psychology, heuristic techniques are effortless, fast to derive new intuitions that explain how humans make decisions, come to judgements, improvise behaviours, and solve problems, particularly difficult problems or when the situation presents available partial information or is stressful. These new intuitions will perform well in most conditions, but in some cases, it will lead to cognitive biases or systematic errors [63] (subsubsection 2.4.7.1).

In the human-robot communication system, the robot partner should be equipped with heuristic techniques to simulate real communication with its human user. As an example, the robot partner can dynamically generate a conversation dialogue according to its surrounding information and its conversation context with the user in real time. Hence, heuristic techniques are the ideal areas to be explored in human-robot interaction because of the fast solution (i.e. conversation dialogue) generation feature. For example, in Chapter 7 the robot partner is equipped with a daily conversation system that is based on efficient heuristic techniques to generate new intuitions in its conversation dialogue. These new intuition generations are based on prior knowledge and environment context information in the working memory. It is done without much effort of processing with the small memory capacity of the working memory.

2.4.7.1 Cognitive Biases or Systematic Errors

Cognitive bias is a behaviour of variation in one's judgement, by which assumption is made about other individuals or conditions in an irrational manner [70]. Another view is that cognitive bias is the "subjective reality" from one's perception of one's sensory input [20]. A person's creation of his or her reality may dominate his or her action and behaviours in the society [20]. In sum, cognitive bias may result in irrational interpretation, imprecise judgement, perceptual distortion or irrationality [11, 83, 179]. Péter and János [54] had proposed computational intelligence approach for corrective mechanism for biases cognitive during cognitive decision-making. Their work [54] had investigated the links between computational intelligence and cognitive biases in the optimisation point of view.

Gerd and Daniel [64] suggested that certain cognitive biases are apparently adaptive behaviours. Hence, these cognitive biases could trigger more effective actions in certain situations. Besides, cognitive biases may arise faster decisions in a condition where timeliness is more important than precision as discussed in the concept of the heuristic technique [176]. As an example of a critical situation, if a person is trapped in a forest fire and the person cannot outrun the forest fire because the wind is blowing in one direction, the person can quickly derive a solution such as hiding in non-flammable fields instead of keeping on running.

Furthermore, cognitive biases can also be viewed as scope extensions (reactive control) of standard actions during time-critical survival situations. For example, in the above case, instead of randomly searching for non-flammable areas (proactive control), it is better to shelter in the fields already burnt by the fire further in front (reactive control), as the advanced burned areas will not able to subject to fire again. This action is not the person's standard actions of escaping from danger, but a display of cognitive bias as a scope extension of standard actions (reactive control) deriving agent's new intuition. Hence, cognitive biases are viewed as agent's heuristic behaviour [149] (subsection 2.4.7). In this example, cognitive biases are linked to survival behaviour as mentioned by Pfeifer's [135] intelligence definition 1.5.1.

Cognitive biases are also described as the robot partner's adaptive behaviours [64]. According to relevance theory [152] (subsection 2.5.4), the robot partner and its human user thinking processes (or mind) cannot be directly exchanged in a conversation. Hence, the robot partner may create some cognitive biases during its "trial and error" conversation dialogue with its human user. The reason is that information on the thinking process of the robot partner's human user is only partially available. However, the robot partner's suggestions will be slowly improved (adapted) during its working memory dynamic optimisation as discussed in Chapter 5. Hence, the robot partner's cognitive biases adaptive behaviour is to "make a wild guess" of its human user thinking process or the human user's needs. As a result, these cognitive biases may create action errors but they are systematic errors in the intermediate process of deriving an ideal solution or merely in the process of trials and errors.

2.4.7.2 Cognitive Load

In cognitive psychology, *cognitive load* is about the amount of mental effort allocated to one's *working memory* (subsubsection 2.4.4) processing. The cognitive load theory was coined during a case study of problem solving by John Sweller [165]. Sweller also claimed that instructional design could be utilised to decrease cognitive load for the learner. Instructional design refers to the learning environment design for the learner. In other words, the environment setting plays a significant role in influencing the learning behaviour as stressed by Neisser [126, 127].

In definition 1.8.1, dual mechanisms of cognitive control in working memory are the essential consideration for agent cognitive intelligence behaviour as explained by Braver et al. [26]. Furthermore, dual mechanisms of cognitive control [26] theory is similar to cognitive load [165] theory because both also explains the processes in agent's working memory. Therefore, cognitive load is considered as the same with dual mechanisms of cognitive control [26]. The reason is both theories also describes the agent's cognitive processing as ultimately occurring in the working memory instead of in other memory types, according to these findings [26, 104, 149, 165, 176]. However, the terms cognitive load and dual mechanisms of cognitive control will be used interchangeably because they are referring to the same cognitive process in the agent's working memory.

2.5 Philosophical Models: Literature Review

The philosophical models perspective of the embodied cognitive intelligence topic is explained with abstract concepts and the understanding of embodied cognitive intelligence. Philosophical models perspective is different from the psychological models point of view because psychological models reassemble closely to the biological behaviours from experiment observations.

On the other hand, philosophical models of embodied cognitive intelligence are typically expressed in the form of an analogy of natural events. Furthermore, most of the philosophical models provide a categorization of behaviours for explaining the embodied cognitive intelligence events [89]. Philosophical models are necessary to simplify the understanding of embodied cognitive intelligence phenomena.

2.5.1 Perception and Action Models

Perception and action model is one of the fundamental understandings of agent's cognitive intelligence behaviour [142]. According to Brady's cognitive intelligence definition 1.6.5, cognitive intelligence is the agent's intelligent connection of perception to action.

Perception and action model in this research had extended into four main modules: perception, situation, intention and action modules. Figure 1.4 explains the control flow of these four modules. Firstly, an agent's perception module is an input perceiving module that detects concepts from the environment and label the concepts appropriately (i.e. visual concept detection). Next, the situation module stores both the currently detected concepts from the environment and the recalled reference memory into the agent's working memory. Then, the agent's intention module is responsible for keeping the agent's current goal or its objective. The agent's intention is constructed with the information currently stored in agent's working memory. Lastly, an agent action module is the agent's ability to react to the environment (i.e. walking) based on its intended intention.

Our focus is to model the perception and action model on its transitions phenomena between situation and intention in dual mechanisms of cognitive control [26] (definition 1.8.1). The dual mechanisms of cognitive control consist of proactive control and reactive control mechanisms for agent's cognitive intelligence behaviour. The proactive control is referred as the optimisation of agent's working memory towards its intention. On the other hand, the reactive control is described as the situation triggers the agent's new intuition (intention) creation behaviour.

2.5.2 Affordance Theory

Definition 2.5.1. *Affordance*, referring to a particular agent, is a property of the environment that permits the agent to engage in some action [62].

In Gibson's work [62], the affordance theory (definition 2.5.1) explains the importance of the environment's information that influences the agent's actions. For instance, if a person sees a train arrives at the station, then the person is only able to execute (or afford) his or her action to board the train. In the vice-versa situation, the agent's ability to afford any given action is highly influential to the agent's perceptual orientation of the environment. For example, if an adult sees a small children chair, the adult will not perceive it as chair (perceptual orientation) because it is too small to be seated (agent's ability). Thus, the adult will not easily to have any intention to sit on it. Furthermore, according to Gibson [62], he also explains the agent's intention influences the agent's perception orientation of the environment. For example, when a person is driving (current intention), the person will not easily to be orientated to read any long paragraph of text (perception orientation) when he is driving.

About this research, the robot partner's perception orientation of the environment is related to working memory because working memory that stores currently perceived environmental information. Moreover, the robot partner's heuristic behaviour [149] (subsection 2.4.7) that constructs its new intention is based on perceived information in its working memory. The formation of robot partner's new intuition (intention) is highly influenced by contents in robot partner's working memory (currently perceived perceptions in the environment) according to heuristic behaviour [149]. For instance, the robot partner is having a conversation about a sports topic (current intention) with an elderly person; the robot partner should have some barrier to change the conversation topic to food topic because the robot partner's working memory is currently stored information (perception orientation) about the sports topic. In summary, it is effortless to explain the theory of affordance with working memory because these issues are related to cognitive intelligence.

2.5.3 Theories of Direct Perception and Direct Learning

Definition 2.5.2. *The theory of direct perception* is the perception peculiar to the properties of ambient energy arrays [77].

Jacobs and Michaels presented the idea of *direct perception* [77] (definition 2.5.2), as opposed to elementarism, that explains learning regarding ambient energy arrays and according to the theory of affordance [62] (subsection 2.5.1).

To evaluate direct learning empirically, they had proposed the notion of information space to analyse and interpret from the perspective of direct learning. Information space is the points for ambient energy patterns; paths constitute the change due to learning, and vector fields describe information that guides learning.

Definition 2.5.3. *The theory of direct learning* describes a broad range of phenomena in ecologically relevant and informationally rich environment as well as in simpler experimental situations [77].

They also proposed the theory of direct learning (definition 2.5.3) that explains agent's learning in high-dimensional natural data and the informationally rich environment. Furthermore, Neisser [126, 127] also emphasises the importance of natural data in modern cognitive intelligence experiment settings. Hence, we adopt the notion of natural data perception detection in our experiment setting. The robot partner visual perception detection of natural data environment is represented as visual concept detection module [80, 81, 147] at Chapters 5 and 7.

2.5.4 Relevance Theory

Definition 2.5.4. The relevance theory that explains an essential feature of most human communication, both verbal and non-verbal, is the expression and recognition of intentions [152].

This theory, proposed by Wilson and Sperber [152], is the detailed explanations of Grice's studies in the intentions of words [66, 67]. The relevance theory explains the encoding and decoding of intentions in a verbal and non-verbal conversation. Grice and White [66, 67] sought to explain intentions in an oral and non-verbal conversation; by observing the conversation's contents following a co-operative principle and maxims of *quality* (truthfulness), *quantity* (informativeness), *relation* (relevance) and *manner* (clarity).

This research argues that agent's heuristic technique [149] (subsection 2.4.7) forms the intention for solving a problem during agent's reactive control [26] (definition 1.8.1) conditions. Hence, the intention of the robot partner to address a problem is constructed (encoding) by the concepts perceived in the robot partner's working memory (example 2.4.2). On the other hand, the decoding of the robot partner's intention is categorised as the optimisation process (proactive control that agent's intention influences the situation in the robot partner, section 1.8). Chapters 5 and 7 explain the intention encoding and decoding processes.

2.5.5 Mutual Cognitive Environment

Definition 2.5.5. *Mutual cognitive environment* is the shared cognitive environment for agents [84, 92].

According to the relevance theory [152] (subsection 2.5.4), human communication is limited by the environmental boundary. In other words, a person's thoughts cannot be directly transmitted to each other. However, the thoughts are shared between two people with communication mediums such as sound and visual. Therefore, each has his or her cognitive environment based on the comprehension of the limited available information perceived with these communication mediums. Hence, the *mutual cognitive environment* is an extension of the relevance theory [152] that seeks to understand and improve communication.

The mutual cognitive environment is also the understanding of the current situation (definition 1.8.1) between different agents. We illustrate the concept of the mutual cognitive environment in following Example 2.5.1.

Example 2.5.1. As an example of a mutual cognitive environment, two individuals (person A and person B) are having conversations. Then person A tells information X to person B. Hence, the shared information X is the mutual cognitive environment that both persons are aware of it. In short, information X is stored in both persons working memory to maintain the mutual cognitive environment.

In a view to supporting the human-robot communication for the elderly people, the robot partner's working memory is needed to store and process its environment context information. The environment context information is an important factor to be considered in cognitive intelligence as mentioned by Neisser [126, 127]. In Chapters 5 and 7, we discuss the proposed spiking reflective processing to implement artificial working memory module into robot partner.

2.5.6 Structured Learning

Definition 2.5.6. *Structured learning* focuses on the importance of interdependent linkages between structurally coupled learning modules and adaptive learning, behavioural learning, and cognitive learning modules [86, 87, 90, 91].

Kubota et al. [86, 87, 90, 91] proposed the concept of *structured learning* for the robot partner that emphasises the interdependent linkages between structurally coupled learning modules for the ABC of learning (subsubsection 2.5.6.2). Baar also emphasised the modular access of information that can be referenced into the agent's working memory in his global workspace theory [5] (subsection 2.5.7).

In the embodied cognitive intelligence point of view, stress and working memory modules reassemble the adaptive learning module (subsubsection 2.5.12) in structured learning. The reason is adaptation learning is one of the ability to survive [135] by adapting to the robot partner's new environment. Furthermore, Attar and Müller had argued emotion, adaptation and survival are highly co-related and empirically supported [74]. For example, if an agent is in stress after the agent constantly failed to perform a task, the agent will try to find a solution in greater context to adapt to the agent's environment to reduce its stress level. Therefore, the agent's working memory retrieval performance scope is needed to be widening to support the greater context of working memory search for the agent's new solution. According to Lupien et al. [104] the working memory retrieval performance scope can be widened during the agent's middle-stress conditions. Therefore, our proposed robot partner's models in Chapters 3, 5 and 7 are integrated with stress and working memory components to achieve the robot partner's survival ability.

2.5.6.1 ABC of Intelligence

Definition 2.5.7. *The ABC of intelligence* represents three different levels of intelligence that are artificial intelligence, biological intelligence and computational intelligence [53].

Definition 2.5.8. *Artificial intelligence* has been developed to describe and build intelligent agents that perceive an environment, make appropriate decisions and take actions [142].

Definition 2.5.9. *Biological intelligence* is defined in physiological terms on the basis of the anatomical structures involved, and with the consideration of mechanisms of learning and memory [32].

Definition 2.5.10. *Computational intelligence* tries to construct intelligence by the bottom-up approach using internal description. Computational intelligence is also a methodology involving computing that depends on numerical data [60, 89].

The ABC of intelligence [53] is a multidisciplinary view of intelligence. Multidisciplinary understanding of intelligence is crucial for the development of robot partner's cognitive intelligence. The reason is that the robot partner's cognitive intelligence development requires the accumulation of these multidisciplinary understandings. For this research, an additional philosophical point of view is added on top of these three points of view. The philosophical point of view is to investigate the robot partner's understanding of cognitive intelligence.

2.5.6.2 ABC of Learning

Definition 2.5.11. The *ABC of learning* refers to adaptive learning, behavioural learning and cognitive learning [89].

Definition 2.5.12. *Adaptive learning* requires an explicit interaction with the environment. If the environmental conditions change, the robot partner needs to react accordingly with the identified differences [89].

Adaptive learning (definition 2.5.12) is reassembled as part of stress response system. The reason is that stress response system has the features of an adaptive system for the agent to survive [135] by adaptation. For example, Attar and Müller had argued that adaptation, emotion, and survival are related and they are empirically supported [74]. For example, if an agent is not able to find a solution to a problem, the agent will raise its stress level for wider access to its working memory retrieval performance [104] to construct its new intuition with heuristic technique [149] (subsection 2.4.7).

Definition 2.5.13. *Behavioural learning* refers to learning skills that acquire behaviours based on sensory-motor coordination [89].

Behavioural learning (definition 2.5.13) is the learning ability that reinforces the learned skills of the robot partner in its static environmental states. For example, via the robot partner static path optimisation [24] where the optimal path (learned skills) is found and the optimal path solution is reinforced for its correctness with reward. On the other hand, adaptive learning requires the robot partner to react accordingly when the environment states are not stationary [171]; this will be discussed in Chapter 3.

Definition 2.5.14. *Cognitive learning* refers to learning skills that acquire language, knowledge and perceptual information [89].

Cognitive learning (definition 2.5.14) on learning skills of perceptual information is presented as deep learning visual concept detection in Chapters 5 and 7. For example, the cognitive learning is a learning ability that robot partner can translate natural data environment information into detected meaningful concepts. Then, these detected concepts will be stored in the agent's working memory for cognitive load processing [165] (subsubsection 2.4.7.2).

2.5.7 Global Workspace Theory

The Baar's global workspace theory of cognitive intelligence explains the agent's working memory as a theatre stage [5]. He uses a theatre metaphor to explain his understanding of the human mind and the related cognitive intelligence processes in the human mind. The global workspace theory is an important theory that specifically emphasises the importance of working memory in agent's cognitive intelligence behaviour. Hence, we quoted his theory's main concepts [5] in a list that emphasises the importance of working memory in the centre of his discussion:

1. Working memory is like a theatre stage.
2. The players on stage: the contents of conscious experience.
3. The spotlight of attention. Conscious contents emerge when the bright spotlight of attention falls on a player on the stage of working memory. However, the spotlight has a fringe.
4. Contexts operate behind the scenes to shape events on stage.
5. The audience.

Furthermore, the interdependent linkages of structured learning's modules [86, 87, 90, 91] (subsection 2.5.6) have many similarities with Baars's global workspace theory [4, 5, 6] (subsection 2.5.7). The learning module can be recalled during the time of need by loading the information required to the working memory (definition 2.4.2). However, Baars's model [4, 5, 6] did not consider agent's stress emotion and its effect on the working memory retrieval performance as indicated by Lupien et al. [104]; thus, this gap is addressed in Chapters 3, 5 and 7.

2.5.8 Scaffolding Minds Theory

Definition 2.5.15. The *scaffolding minds* theory is a problem-solving approach incorporating problem's complexity reduction by environmental information support [34].

The *scaffolding minds* theory was introduced by Clark [34]. It refers to the use of environmental information support for complexity reduction in problem-solving approach. For example, yellow stickers at the workspace are tools to remind the user of important information about his or her tasks. The yellow stickers also act as the tools for reducing the user's cognitive load [165] (subsubsection 2.4.7.2) efforts on problem-solving. Hence, the user can reduce his or her working memory from overloading with the help of these yellow stickers.

Scaffolding minds theory is an important philosophical concept because it also refers to the mechanisms of human's working memory with natural data environment support. The working memory stores the currently perceived natural data from the environment. Then, the dual mechanisms of cognitive control [26] (definition 1.8.1) will process the information stored in working memory. Furthermore, natural data environment experiment settings were emphasised by many modern cognitive psychology researchers [77, 126, 127].

Development of the robot partner's embodied cognitive intelligence also needs to consider this perspective where the environment perceptions provide support for its embodied cognitive intelligence. For example, the robot partner's working memory will temporarily store the currently perceived natural data from the environment into its working memory. Then this perceived information in the working memory would enable heuristic [149] or new intuition creation behaviours.

2.6 Computational Models: Literature Review

The literature on computational models covered here refers to that involving algorithmic processing and computing hardware for robot partner cognitive intelligence processing. The three main cybernetic categories identified are McCulloch's cybernetics, Wiener's cybernetics and Turing's cybernetics.

2.6.1 McCulloch's Cybernetics

McCulloch's cybernetics is the study of computational theory in the perspective of neuroscience [3]. In Chapter 5, we use the deep neural network approach for the robot partner's real-time image concept detection module [147]. We also utilised the Spiking Neural Network (SNN) that exhibits many interesting properties for the robot partner's embodied cognitive intelligence and specifically for its new intuition creation behaviour.

The robot partner's new intuition creation behaviour requires a specific moment that is suitable for such event. In Chapter 7, we name such behaviour as *spiking reflective processing* during the SNN [61] exceeded a certain threshold for a fires condition.

2.6.2 Wiener's Cybernetics

Wiener's cybernetics is the study of computational homoeostasis control systems of artificial life. The homoeostasis control system is a system that based on the concept of feedback that maintains the internal equilibrium (maintaining internal control and balancing it to suitable levels) [183].

Human's stress response system (subsection 2.3.1) is an example of homoeostasis control system. According to Yerkes and Dodson [186], only in the middle-stress arousal condition will an agent exhibit full embodied cognitive intelligence performance. For instance, if an agent is hungry and it causes higher stress level than normal condition. The increased stress level in the agent will enable broader working memory retrieval performance to construct new intuition to search for food. Hence, the agent's ultimate goal is to maintain its middle-stress level to achieve internal equilibrium for its survival [135] (definition 1.5.1). In this example, the agent's act of constantly balancing its stress level will benefit itself to be more efficient in search for food according to Yerkes and Dodson law on stress [186]. Furthermore, the agent also needs to increase its stress level in the time of desperate and reduce its stress level if there are no survival needs.

Therefore, the ideal robot partner's embodied cognitive intelligence should be a system based on internal control of stress arousal, working memory and feedback mechanisms.

2.6.3 Turing's Cybernetics

The Turing's cybernetics is the study of intelligence based on computation, calculation and machines [175]. Turing's cybernetics approach tries to emulate human intelligence through a computational algorithm in an anonymous-text-based conversation test. It was later known as the *Turing's Test*. For example in Turing's test experiment settings, a human tester will have a conversation with an agent by typing the text via keyboard to the computer machine. The machine will randomly represent human or a computer artificial intelligence. The task of the human tester is to differentiate the agent whether it is a human or a computer machine.

However, computational algorithm alone is not enough to understand the complex human embodied cognitive intelligence system (definition 1.6.7). Hence, the study of human's stress response system may answer many questions about the unknown phenomena in human embodied cognitive intelligence behaviours. For instance, what is the condition to initiate new intuition for the agent? Therefore, we need to have an extensive understanding of the embodied cognitive intelligence functionality before proposing new embodied cognitive intelligence model.

In this research, a computational model is suggested as the evolutionary computation optimisation algorithm for the robot partner's working memory optimisation in Chapters 5 and 7.

2.6.4 Behavioural Control Model

Definition 2.6.1. The *behavioural control model* refers to persona enhancements and quantum transfer decision logic [44].

The behavioural control model [44] uses the quantum transfer of decision construction for the robot partner's persona changes. According to Simon et al. [44] the changes of agent's persona in the behavioural control model are needed to adapt to its environment changes. His research objective is to find the robot partner's free will behaviour with a stochastic assignment of persona with quantum physic theory. However, the quantum transfer decision logic is a pure engineering approach and it has no empirical biological literature to support the agent's cognitive intelligence behaviour.

In Chapter 7, our proposed robot partner's embodied cognitive intelligence behaviour is modelled with Braver et al.'s [26] dual mechanisms of cognitive control (definition 1.8.1). The reason is the dual mechanisms of cognitive control are empirical cognitive psychology understanding of human's embodied cognitive intelligence.

Furthermore, the proposed model also emphasises the importance of natural data environment experiment settings [77, 126, 127] in cognitive intelligence research. The focus of this research is to find the robot partner's embodied cognitive intelligence behaviour in a natural data environment. Our proposed model in Chapter 7 is applied to the environment that is not as stagnant (only in bartender activity) as described in the gin and tonic test in Example 2.4.1 [43]. For instance in Chapter 7, robot partner experiment is conducted with many different users.

2.6.5 Reinforcement Learning with Stress Model

Luksys and Sandi [103] proposed a reinforcement learning model to explain the Yerkes and Dodson's [186] inverted-U-shape phenomenon. They discussed the exploitation factor beta and discounting factor gamma to form the inverted-U-shape graph. However, their experimental simulation did not have the natural data stimuli that cause the changes in stress level and working memory retrieval performance to the robot partner as indicated by Lupien et al. [104], as when, for example, the robot partner encounters animal disruptions to its normal operation. Furthermore, Neisser [126, 127] emphasises the significant of natural data environmental settings for cognitive intelligence experiment.

The Markov Decision Process (MDP) [18, 163] with stress and working memory model implementation is applied and discussed in Chapter 3. The reinforcement learning stimulation in Chapter 3 includes many different types of stressor obstacle to the robot partner.

2.6.6 Evolutionary Computation Models

In computational intelligence [136] research, evolutionary computation [45] is a sub-research field of computational intelligence. Evolutionary computation is a type of stochastic statistical optimisation approach that models the features of natural adaptation behaviours. For example, bacterial mutation behaviour is a natural adaptation evolutionary computation model [21, 22, 23, 125].

Braver et al. [26] had proposed proactive control (definition 1.8.1) for agent's working memory active optimisation towards its intention. The agent's working memory is modelled as the population for optimisation. For example, if the agent were having a conversation about food topics and then changed to sports topic, the agent's working memory should be able to adapt slowly to sports instead of food topic. In this example, the agent's working memory should store more concepts about sports than food topic.

In the stress-based model for this research, the robot partner's working memory is a condition for optimisation because of proactive control [26] condition. The working memory is optimised toward its intended goal (cognitive product). Chapter 4 will discuss the improvements on the evolutionary computation optimisation algorithm by reducing the effects of inbreeding depression of the population [79].

Furthermore, the robot partner's working memory optimisation will be at its peak performance during the robot partner's middle-stress condition, according to the Yerkes and Dodson inverted-U stress condition [186].

2.7 Chapter Summary

In this chapter, the literature on the biological, psychological, philosophical and computational research related to the research topic of this thesis was reviewed. The links between these four research areas were discussed with the focus on stress response system and working memory perspectives. The potential gaps in these four different research areas were identified with synthetic modelling methodology [135] (definition 2.1.1).

In summary, the development of the robot partner's embodied cognitive intelligence requires a multidisciplinary approach for a thorough understanding of these four research areas. On top of that, we discovered in these four research areas literature exist with empirical evidence to support their mutual relationship in the stress response system and working memory point of views. Therefore, agent's stress response system and working memory are the crucial gaps for robot partner's embodied cognitive intelligence research.

In the following five chapters, the gaps in these four research areas in the literature will be addressed, in particular with the stress response system and working memory model perspectives. In the next chapter, the work on the robot partner's reinforcement learning based on the stress model will be discussed [171].

Chapter 3

Stress-inspired Working Memory for Robot Agents

3.1 Introduction

This chapter investigates research question 3 (RQ3) in subsection 1.7.3, "Can we improve the state of the art cognitive intelligence for robot partners by applying biological principles?". About Chapter 2, this chapter is an attempt to develop a stress-based working memory in a simulated agent in path planning problem. According to the subsection 2.4.6, the agent's working memory retrieval performance is related to its stress arousal level [106]. The agent's current stress arousal level also determines the retrieval scope of its previous actions. Furthermore, its current stress arousal level also limits its action. We will discuss the overview of Section 3.2 new intention or new intuition in this chapter as a batch of actions.

The biological system is known to inspire both intrinsic and extrinsic motivations. Extrinsic motivation it based mostly on environmental conditions; it has had been well investigated by reinforcement learning methods. On the other hand, the intrinsic motivation of the agent will be investigated in this chapter. In our opinion, intrinsic motivation is a much more interesting topic to be explored. For example, what are the possible intrinsic motivations that may drive an agent to perform certain tasks?

In this chapter, the possible intrinsic motivation of the agent will be investigated. A novel biological-inspired intrinsic motivation model that is based on Yerkes and Dodson's [186] stress curve theory is proposed. The stress feedback loop will affect the agent's working memory retrieval performance capacity. The agent's stress feedback and its working memory signals are input into a fuzzy logic decision-making system. Then, it depends upon the best suitable action for the agent to perform after considering the current best action policy.

The experimental simulation results indicate that the proposed model is significantly better concerning the agent's learning performance and stability when compared with the existing state-of-the-art reinforcement learning approaches in non-stationary environments. In addition to that, the proposed method can also effectively deal with larger non-stationary problem domains.

3.2 Overview

Definition 3.2.1. *Intrinsic motivation* is the internal manipulation drive needed for an agent to persistently solve problems without any external stimulation or reward [69].

Intrinsic motivation in agent was a term first mentioned by Harlow [69]. The concept of applying intrinsic motivation to reinforcement learning is current research trend. On top of that, intrinsic motivation in the agent is very useful in a non-stationary environment, especially when the environment is optimised around emotions and complex interactions. In this chapter, a novel model that is based on biology stress is proposed.

In early research on reinforcement learning model-free approaches such as the Q-learner [182] were investigated. However, *sample inefficiency* is faced by model-free approaches [73]. *Sample inefficiency* refers to an agent requiring a huge training sample to find a solution. A current trend in reinforcement learning is to use model-based intrinsically motivated methods [150].

Figure 3.1 is a comparison diagram showing the characteristic differences between a model-free and a model-based intrinsically motivated reinforcement learning approach. The main feature of a model-based approach is the internal world memory representation of the agent's mind.

The agent's internal world memory representation of the environment will be considered before any action is selected upon or carried out. Sensor information from the agent's external sensor does not directly affect the agent but it is integrated as part of its internal world memory model. This proposed model is similar to that of Singh et al. [150] but the proposed model have effects on the agent's internal world memory with stressors from the environment.

Based on the Yerkes and Dodson's [186] initial discovery of the stress curve theory, the agent's maximum cognitive performance is in the middle-stress condition. The stress arousal has the inverted-U shape relationship with the agent's cognitive performance. Next, group actions can be categorised as either deliberative sets (low-stress)

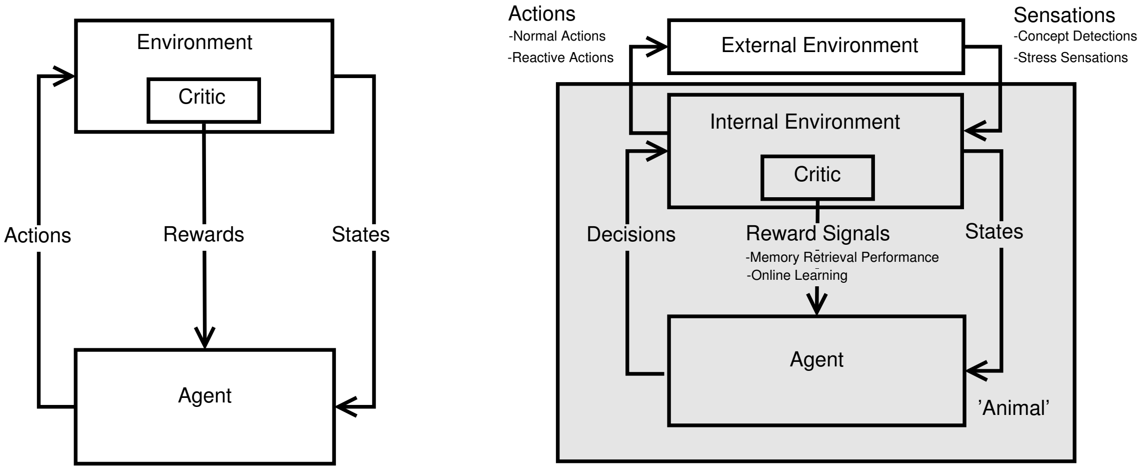


Figure 3.1: Model Comparison between a Model-free Approach (left) and an Intrinsically Motivated Reinforcement Learning Model [150] (right). *©2010 IEEE. The IEEE does not require individuals working on a thesis to obtain a formal reuse license to reuse the figure content.*

or reactive sets (high-stress). During high-stress situations, the agent may ask for help to reduce the stress imposed on it that prevents it from performing its tasks.

On the left diagram of Figure 3.1 explains a model-free approach where its critic term is represented as reward function from the external environment. On the other hand, on the right of Figure 3.1, the reward signals of an animal are presented. The reward signals in an intrinsically motivated model refer to the rewards that are triggered by the agent's internal (intrinsic) neural signals [150]. This diagram on the right in Figure 3.1 had been improved from Singh et al. [150] with additional biological stress perspectives for this research.

The agent's input sensors can be placed into two different categories, i.e. *concept detection* and *stress sensation*. The agent may experience *pain* (danger signals) in a stressful environment with its stress sensation represented as environmental feedback in this chapter. Next, the agent's image concept detection is represented as a vector of three detected features that are the *abstract class*, *class* and *concept*. These three features vector for our model is needed to simulate the virtual environment's noise for the agent's sensors. For example, if the environment's noise is strong, the agent's sensor detection accuracy is reduced and only abstracts concept can be detected.

Furthermore, the action output types for the agent can be categorised into two, i.e. *normal* (non-stressful) or *reactive* action types. For example, normal action is normal movement and reactive action is the agent asking for help. Next, in the model on the right of Figure 3.1, the centre of the model is the agent's internal world representation. The internal world representation consists of previous actions stored in the agent's working memory and its online neural network model.

In this chapter's proposed model, the agent's online neural network is needed to predict future actions from its previous correctly executed actions. Furthermore, based on Lupien et al.'s [104] discovery of human stress arousal relationship with human working memory retrieval performance, an agent's working memory retrieval performance is also influenced by the agent's stress arousal conditions.

3.3 Motivation for Experiment

The work [161] is a very interesting research study and it is relevant to my Ph.D. work.

The objective of their research is to simulate the emergence of mind within the robot, this is achieved by conducting a series of self-preservation experiments and interpreting the results. This work also describes and uses U-shape stress functions to adapt the robots behaviour towards achieving the desired self-preservation goals. However, they only apply these stress-based ideas in a wider context and to different aspects of the "mind". They did not specially discuss, implement or experiment with the specific component of the "mind" called working-memory, which I argue, is directly related to planning and decision making of an agent.

Although U-shape stress functions are thought to operate over different areas of the "mind" I am specifically interested in its role of regulating one specific aspect of the mind, that of working memory. My research work has developed an SBMRP model that focuses on applying stress models to regulate working memory of an agent. The model and aims in my work are a substantially different when compared to the work [161].

The biological stress response system within an agent. For example, the hypothalamic-pituitary-adrenal (HPA) axis [133], is designed to solve uncertainty in dynamic environmental problems. According to Mason [111], unpredictable changes in a dynamic environment will cause relative stress (subsection 2.4.2) to an agent. This phenomenon is the stimulation for this chapter to propose a biological stress-inspired model for the agent to solve its dynamic environmental reinforcement learning problems. The main reason to use the biological stress-inspired model is because the biological stress response system represents many similarities with the intrinsically motivated model. Both of them have an internal world or memory representation of the environment.

In the *Scaffolding Minds* [34] perspective (subsection 2.5.8), it emphasises on continuous concept detection for agent's decision-making process, the agent's working memory will store the continuously detected concept. Thus, the stored arbitrary concepts in the agent's working memory can construct new intuition [126, 127] and it resembles many *Scaffolding Minds* [34] theory's attributes.

Clark [34] also argued that cognitive intelligence could not exist without considering the intelligent agent's body. In other words, the existence of the agent's cognitive intelligence is more than just the brain as mentioned by Pfeifer [135]. In this chapter, this phenomenon is defined as embodied cognitive intelligence (definition 1.6.7) [135].

In other words, the agent's biological inspired stress model and its actions are also considered in this embodied cognitive intelligence proposal. Hence, the agent's total executable actions are constrained by its body stress arousal states and its environmental states according to the scaffolding minds theory. For example, in an event of stress for the agent, the agent will trigger its *allostatic process* [117] internally to enable it to execute extraordinary actions such as shouting for help and moving more randomly. These allostatic processes are not activated during normal environmental conditions where is no stressor in the environment. Hence, the agent's action-state complexity is maintained by its stress arousal state which determines its actions under different stress conditions. In this way, the agent's action-state complexity can be minimised to select better its action.

In Yerkes and Dodson's [186] the significant relationship between stress arousal levels and cognitive performance has been discussed in subsection 2.4.3. Furthermore, in this subsection, Lupien et al. [104] explained the stress arousal relationship with the working memory retrieval performance. In this chapter is introduced a more refined version of Yerkes and Dodson's curve, which is the Hebbian version of the stress curve graph (Figure 3.2).

The stress curve relationship in Figure 3.2 is used in the model proposed in this chapter because the agent's working memory retrieval performance can be estimated with the agent's stress level. Hence, the level of agent's cognitive processing will be based on Yerkes and Dodson's [186] stress law as referred to in Figure 3.2. During the agent's low and high-stress arousal conditions, it will show the lowest working memory retrieval performance; during its middle-stress arousal condition, it will have the highest working memory retrieval performance.

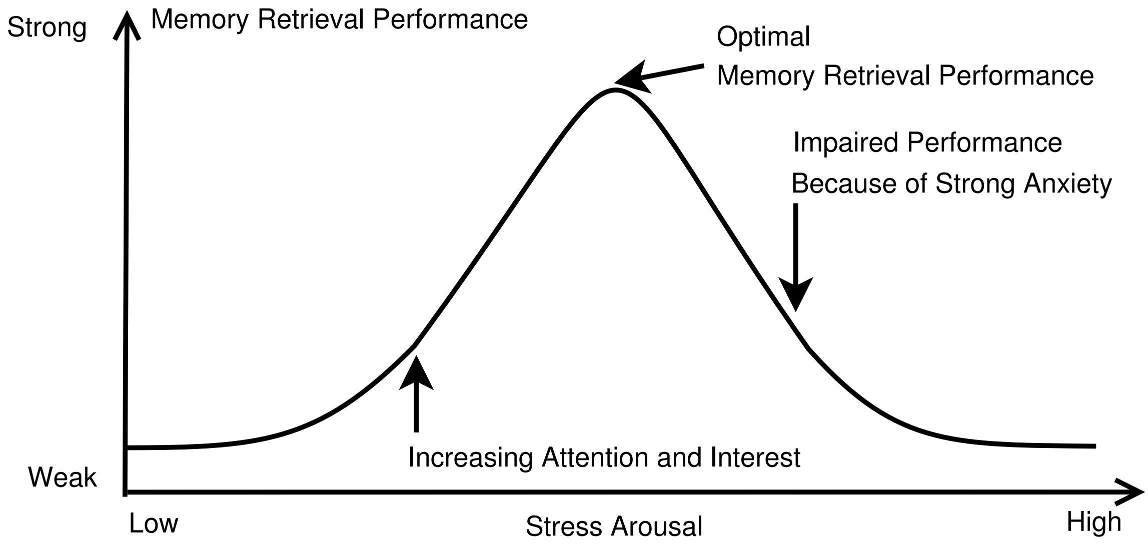


Figure 3.2: Hebbian version of Yerkes and Dodson's Stress Curve [40].

3.4 Objective of Experiment

The objective is to investigate the possibility of stress response system integration into agent's cognitive processing. Therefore, it can improve its path optimisation with the different stress-simulated environment.

3.5 Benchmark Approaches

Markov Decision Process (MDP) [163] model normally represents the problem of reinforcement learning where it is assumed that the last observation is the summary of all previous actions. Hence, it is only necessary to observe the agent's previous state according to the MDP definition to predict the future correct actions.

Reinforcement learning models such as Q-learning [164] have been utilised to learn an optimal action-selection policy for a finite MDP. Q-learning is an off-policy reinforcement learning approach. Off-policy means its learning agent estimate its value function with executed and hypothetical actions (non-executed actions). These reinforcement learning models are proposed to obtain an action-value function that will give a utility of performing a given action in a state. Furthermore, if the action-value function is learned from previous actions, the optimal policy can be known by selecting the highest value action in an action-state space, as follows:

$$Q_{t+1}(s_t, a_t) = Q_t(s_t, a_t) + \alpha_t(s_t, a_t)\left[R_{t+1} + \gamma \max_a Q_t(s_{t+1}, a) - Q_t(s_t, a_t)\right] \quad (3.1)$$

where, S is the set of states, R the reward function and A the set of actions. Furthermore, we denote $Q : S \times A \rightarrow \mathbb{R}$; hence Q is the value set which A and S that are mapped to real value $\mathbb{R}$. Then time step is denoted as t and s is defined as the agent's state. The reinforcement learning action-state complexity is determined by $S \times A$. Subsequently, a is denoted as the agent's action where $a \in A$. A represents the executable actions for the agent and R denotes reward. Then α is defined as the agent's learning rates and γ as the discount factor. Furthermore, R_{t+1} is the reward observed after executing a_t at s_t; hence $\alpha_t(s_t, a_t)$ $(0 < \alpha \leq 1)$ is the learning rate. Therefore, Q-learning or PlainQ can be given by Equation 3.1.

State Action Reward State Action (SARSA) [164] (Equation 3.2) is an on-policy reinforcement learning approach. On-policy means agent estimate its value function based on executed actions only. SARSA is also the complexity reduction version of Q-learning. The reason is both of its max Q selection and policy iteration functions are removed to improve its computational efficiency. Hence, the SARSA approach can perform its computation tasks faster when compared to Q-learning approach when agent's policies (actions) are large enough. Although SARSA proposal is historically older than Q-learning approach. However, SARSA can converge its solution faster when compared to Q-learning under certain conditions (i.e. cliff environment) [164].

In short, SARSA approach is a better solution to reduce the agent's risk of penalties (negative rewards) during agent's learning. However, SARSA approach may not converge the shortest path to its final solution. On the other hand, Q-learning approach will always converge optimal shortest path solution, but its agent's learning process is subjected to more risk of penalties due to agent's exploration behaviours in special environment conditions (e.g. cliff environment) [164].

$$Q_{t+1}(s_t, a_t) \quad = \quad Q_t(s_t, a_t) \quad + \quad \alpha \left[R_{t+1} + \gamma Q_t(s_{t+1}, a_{t+1}) - Q_t(s_t, a_t)\right] \tag{3.2}$$

SARSA and Q-learning are efficient in their computation process; however, they are not *sample efficient* reinforcement learning approaches because they are model-free approaches. Thus they do not have an internal model that retains the previous learned actions and states. The model with internal model-based reinforcement learning approach is used to predict the agent's future actions with minimum sample training.

Sample efficiency as stated by Hester [73] is an important concept. Sample efficiency can enable physical robot applications with reduced sample training. Furthermore it can reduce a large amount of learning time in the physical world.

Subsequently, we introduce a multi-agent reinforcement learning method called Friend-or-Foe Q (FFQ), proposed by Littman [101] (Equation 3.3 for the FFQ model). Littman's [101] FFQ approach utilises the two special Nash equilibria conditions to decide the best reward for the learning agent. However, the special equilibria conditions cause heavy memory utilisation by computing all possible condition pairs for each agent and obstacle agent in a simulated experiment. *Obstacle agent* is an entity acting as the stress-simulated effects in the experiment.

Let's define π as policy and a_1, a_2 are the agent and obstacle agent pairs that need to be computed. Equation 3.3 computes all possible agent pairs conditions for the optimal Q_1, Q_2 values with respect to the state s.

$$Nash_1(s, Q_1, Q_2) = \max_{\pi \in \Pi(A_1)} \min_{a_2 \in A_2} \sum_{a_1 \in A_1} \pi(a_1) Q_1[s, a_1, a_2] \quad (3.3)$$

Adaptive State Focus Q-learning (ASFQ) was proposed by Busoniu et al. [29] for multi-agent reinforcement learning. ASFQ is derived from Q-learner as its base:

$$Q^i_{t+1}(s^i_t, a^i_t) = (1 - \alpha^i_t) Q^i_t(s^i_t, a^i_t) + \alpha^i_t [r^i_{t+1} + \gamma \max_{a^i \in A^i} Q^i_t(s^i_{t+1}, a^i]) \quad (3.4)$$

If i is the agent's identity index, $S = S^1 \times \cdots \times S^n$ is the complete state of concatenation of all the agents' current state vectors. The structure and sizes of the i^{th} agents' Q-tables before and after the expansion are given by:

$$Q^i_{before}(s^i, a^i), \quad \dim(Q^i_{before}) = |S^i|.|A^i| \quad (3.5)$$

$$Q^i_{after}(s^1, \ldots, s^n, a^i), \dim(Q^i_{after}) = |S^1| \ldots |S^n|.|A^i| \quad (3.6)$$

The symbol $|.|$ denotes the cardinality of a set. When $Q^i(s^i, a^i)$ is a good approximation of $Q^i(s^1, \ldots, s^n, a^i)$ then with Equation 3.4 the ASFQ model is expected to converge faster according to Busoniu et al. [29], i.e.

$$Q^i_{after}(\ldots, s^i, \ldots, a^i) = Q^i_{before}(s^i, a^i), where, \quad \forall s^i \in S^i, a^i \in A^i \quad (3.7)$$

On the other hand, based on Equation 3.6, if the agent's state and action dimension are large enough, then the ASFQ method suffers from the exponential increase of memory requirements. Furthermore, the ASFQ processing time is also influenced by the concatenation and cardinality of the set $|S^i|.|A^i|$. As a result, the ASFQ approach needs exponential time to execute each action step. In short, the ASFQ model is unable to handle a high dimensional reinforcement learning environment, especially when the non-stationary environment requires high dimensions of actions to mitigate stress from the environment.

Singh et al.'s [150] proposed intrinsically motivated reinforcement learning unfortunately did not take account of the stressor and non-stationary environment criteria. In the real physical environment the agent may encounter stress during its policy learning.

3.6 Stress Based Memory Retrieval Performance (SBMRP) Framework

The proposed Stress Based Memory Retrieval Performance (SBMRP) framework is built on the Q-Learning (Equation 3.1) reinforcement learning method. This proposed framework is inspired by Herbian's version of Yerkes and Dodson stress curve model [104]. The SBMRP model is based on the agent's working memory retrieval performance that is an inverted-U shape graph relationship to the agent's stress arousal level and its working memory retrieval performance (Figure 3.2).

In this proposed model, the fuzzy logic system is implemented to let the agent select different categories of actions during its various stress conditions. The fuzzy logic system is used to determine the *indefinite boundaries* for the different action categories. There are three defined action categories in the proposed approach, i.e. *cognitiveAction*, *normalAction* and *randomAction*. The output generated from the Q-Learning reinforcement learning algorithm is for the *normalAction* category. Then the output generated from the proposed SBMRP framework is for the *cognitiveAction* category. Lastly, the actions that are randomly generated from all possible actions belong to the *randomAction* category.

Algorithm 1 stressDetection

Function *stressDetection* (*agent*, *concept*)

$\delta = 0$;

//Only obstacle agent will cause stress

If Not Empty Space Detected **Then**

$delta = (randi([1, significant])/factor)\times$

$RestaurantWorldStressTable(concept, 1)$;

Else

$agent.h_{gc} = agent.h_{gc} \times \gamma$ //Stress discount rate;

End If

$agent.h_{gc} = agent.h_{gc} + \delta$ //Include delta stress;

If $agent.h_{gc} > 1$ **Then** //Set $agent.h_{gc}$ upper limit

$agent.h_{gc} = 1$;

End If

If $agent.h_{gc} < 0$ **Then** //Set $agent.h_{gc}$ lower limit

$agent.h_{gc} = 0$;

End If

Return $agent.h_{gc}$; //Return updated stress level value

End Function

The scaffolding minds theory [34] is adopted into the proposed SBMRP framework where the environment feedback and its interactions provide the cues for the agent's next action. The agent stores the newly perceived concepts into its working memory. Then, based on its working memory, it constructs a solution (set of actions) to mitigate its current problems (see $stressMemoryProcessing$).

The proposed model's intrinsically motivated property is implemented in the agent's working memory processing model (see $stressMemoryProcessing$) where it will execute its corresponding actions within the memory retrieval boundary computed by its current stress conditions.

In Figure 3.5, the agent needs to perform persistently a batch of selected actions (cognitive product) from its working memory. All the actions in the batch have to be executed before it is replaced with a new batch of actions. Let's define h_{gc} as the current agent's stress arousal state where h represents hormone and *gc glucocorticoid* (stress hormone). Next, let's define gamma γ as the stress level's discount rate. Then, $randi$ is denoted as the function to generate a random integer in the range within the parameter range. Furthermore, let's denote delta δ as the stress arousal level changes triggered by the obstacle agent, where the δ stress arousal intensity value assignment is based on Table 3.1. The SBMRP framework starts with $stressDetection$ function from Algorithm 3.6.

Subsequently, the $stressDetection$ function assigns the stress arousal changes to the agent's h_{gc} level that corresponds to a different obstacle agent's class. The SBMRP framework's fuzzy logic system will be activated based on two input criteria from the agent to select an action category from three possible action categories with respect to the fuzzy logic system's output. The main reason to have three action categories is because multiple stress input criteria are introduced and they will cause allostasis [117] to the agent.

The three action groups are for three different types of action that are *only executable* by the agent during three different stress conditions limited by the fuzzy logic system. The best cognitive performance or the best working memory retrieval performance, according to Yerkes and Dodson's [186] inverted-U stress curve, is during the agent's medium stress or relative stress condition. Task assignments by the human class obstacle agent usually trigger these medium or relative stress conditions. As an example to illustrate this condition, a manager instructs the agent to perform an unknown working task in a robot restaurant world. The agent will then select randomly a set of actions or cognitive product that is bounded within the agent's working memory (scaffolding mind perspective). During its medium stress condition the agent can freely and safely explore the possibility to construct a set of actions or cognitive product.

During the medium stress state, the agent can safely explore different solutions for the unknown working task because it can still tolerate some mistakes from its actions in such condition.

3.7 Fuzzy Logic System

In the SBMRP framework, a fuzzy logic system is implemented for the selection of action categories. The fuzzy logic system has two inputs, $frustrationRate$ and $stressLevel$ variables, and an output, $actionCategory$ variable. The agent's $stressLevel$ is represented as h_{gc}. The response failure rate from the agent when it interacts with an obstacle agent is named $frustrationRate$.

Besides, it also maintains nine sets of fuzzy logic rules that are predefined for fuzzy inference system in each experiment setting. Each fuzzy logic rule is defined with the same weight of importance. The fuzzy logic system output of the proposed SBMRP framework is presented in Figure 3.4 as a 3D output surface. In Figure 3.3 is shown a membership function setting for the proposed SBMRP framework's fuzzy logic system. The *mean of maximum* defuzzification is selected for the proposed fuzzy logic system output generation,

1. **If** ($stressLevel$ is low) **and** ($frustrationRate$ is low), **then** ($actionCategory$ is normalAction);
2. **If** ($stressLevel$ is low) **and** ($frustrationRate$ is medium), **then** ($actionCategory$ is normalAction);
3. **If** ($stressLevel$ is low) **and** ($frustrationRate$ is high), **then** ($actionCategory$ is cognitiveAction);
4. **If** ($stressLevel$ is medium) **and** ($frustrationRate$ is low), **then** ($actionCategory$ is normalAction);
5. **If** ($stressLevel$ is medium) **and** ($frustrationRate$ is medium), **then** ($actionCategory$ is cognitiveAction);
6. **If** ($stressLevel$ is medium) **and** ($frustrationRate$ is high), **then** ($actionCategory$ is cognitiveAction);
7. **If** ($stressLevel$ is high) **and** ($frustrationRate$ is low), **then** ($actionCategory$ is cognitiveAction);
8. **If** ($stressLevel$ is high) **and** ($frustrationRate$ is medium), **then** ($actionCategory$ is randomAction);
9. **If** ($stressLevel$ is high) **and** ($frustrationRate$ is high), **then** ($actionCategory$ is randomAction).

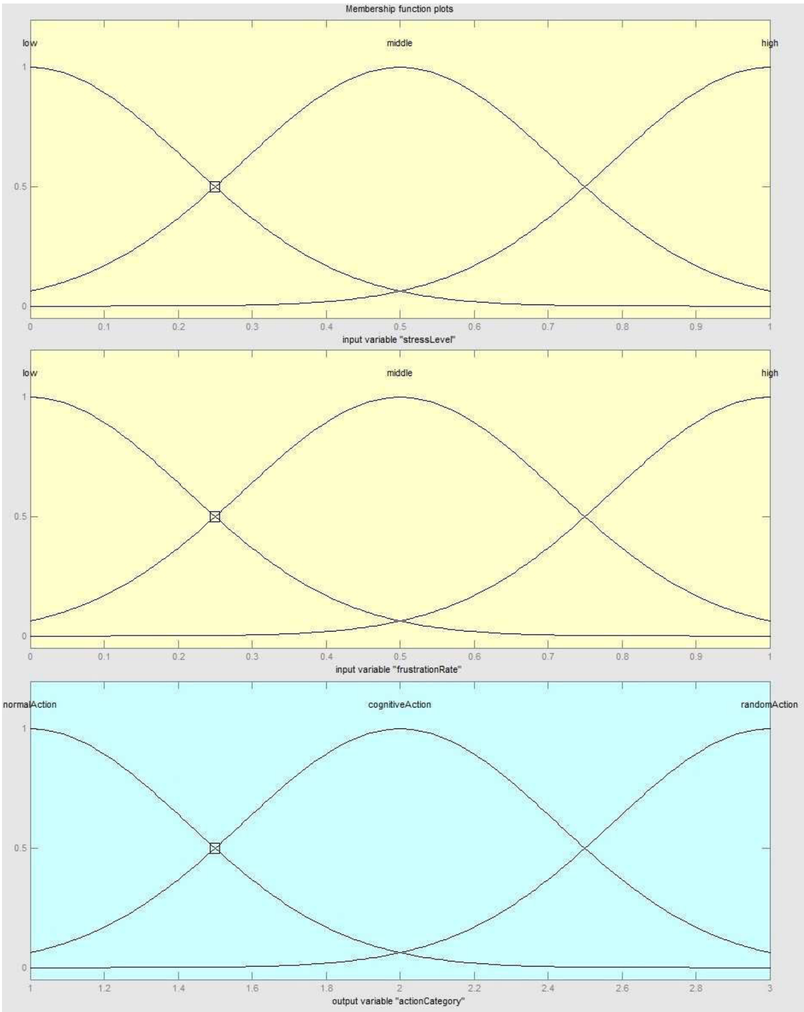


Figure 3.3: Parameter Settings of: (top) $stressLevel$, (middle) $frustrationRate$ and (bottom) $actionCategory$ Membership Function.

Furthermore, the online learning function with feedforward Artificial Neural Network (ANN) is represented as $stressActionSelection$ function. The ANN is defined as $agent.net$. Let's define mu and σ as the mean and sigma parameters for the Gaussian function $gaussmf$ setting.

The areas within the nearest eight grids from the agent are the areas for detecting inputs from the environment. For example, when the agent encounters the obstacle agent within the nearest eight grids area, and the agent executes the correct actions to alleviate the obstacle agent within the nearest eight grids area, and then the obstacle agent will send positive feedback to the agent. In the other conditions, it will send negative feedback to the agent.

The function to process the agent's working memory according to the learning agent's current stress level h_{gc} is implemented in the $stressMemoryProcessing$ func-

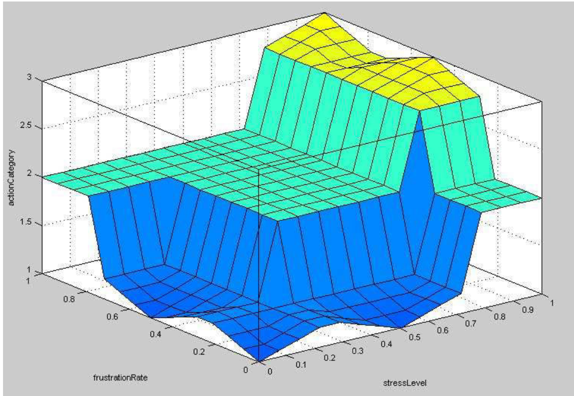


Figure 3.4: Relationship between $frustrationRate$, $stressLevel$ and $actionCategory$ in a 3D Surface Representation.

tion. The agent's working memory retrieval performance is computed by the $gaussmf$ function:

$$mrp = gaussmf(agent.h_{gc} \times 10, [\sigma\mu]) \times 7 \quad (3.8)$$

Next, mrp is defined as the working memory retrieval performance. The Gaussian function $gaussmf$ is needed to calculate the agent's mrp that relates to its current stress arousal level $agent.h_{gc}$. Equation 3.8 shows how mrp is derived with the learning agent's current stress level $agent.h_{gc}$. The agent's memory matrix is denoted by $agent.memory$ that stores the previous executed actions.

The maximum value mrp is simplified to a value of seven because of Miller's Law of Working Memory Capacity. Miller discovered that humans can store seven plus two and minus two (7±2) concepts in the human working memory [121]. However, according to Cowan [38] working memory capacity can be greater than 7 ± 2 concepts. Therefore, the simulated agent's working memory can be extended to 7×7 concepts in this research assumption.

Algorithm 2 stressActionSelection

```
Function stressActionSelection (agent,action)
  If agent received feedback, Then
    For each agent
      //Prepare detected features for ANN training;
    End For
  End If
  For each action
    If agent action had trained with features, Then
      //Activate agent.net and assign output probability;
    End If
  End For
  If sample reached batch total And is feedback, Then
    For each action
      If action is triggered for training, Then
        //Train agent.net with detected features;
        //Reset the sample batch;
      End If
    End For
  End If
  If no activated action Or is first call, Then
    //Assign random action;
  Else
    //Return maximum output probability action;
  End If
End Function
```

The agent's current stress arousal level h_{gc} will cause the *agent.memory* capacity to expand or contract. Then, the batch of actions denoted as *agent.action_set* is represented as the working memory for the agent's actions required to be executed in sequence. The batch of actions *agent.action_set* are given by the red colour action numbers in Figure 3.5. The proposed SBMRP framework is compared with an actor-critic framework [12] in Figure 3.6. The main difference is that the internal working memory representation in SBMRP dynamically extends and contracts according to different stress arousal levels of the agent.

If every old action in the previous action batch is executed, then only the new batch of actions will be selected and assigned to *agent.action_set*. It is to simulate the cognitive product or new idea phenomenon as discussed in Example 2.4.2, Chapter 2. The length of *agent.action_set* variable depends on the mrp value. Figure 3.5 gives further details. The red numbers denote the set of actions selected for batch execution, the black numbers represent the working memory stored of the previously executed actions, and the green numbers indicate the new action assigned to the agents *agent.memory*. The agent's stress arousal level $agent.h_{gc}$ will change according to its working memory retrieval performance mrp scope as represented by the different box sizes.

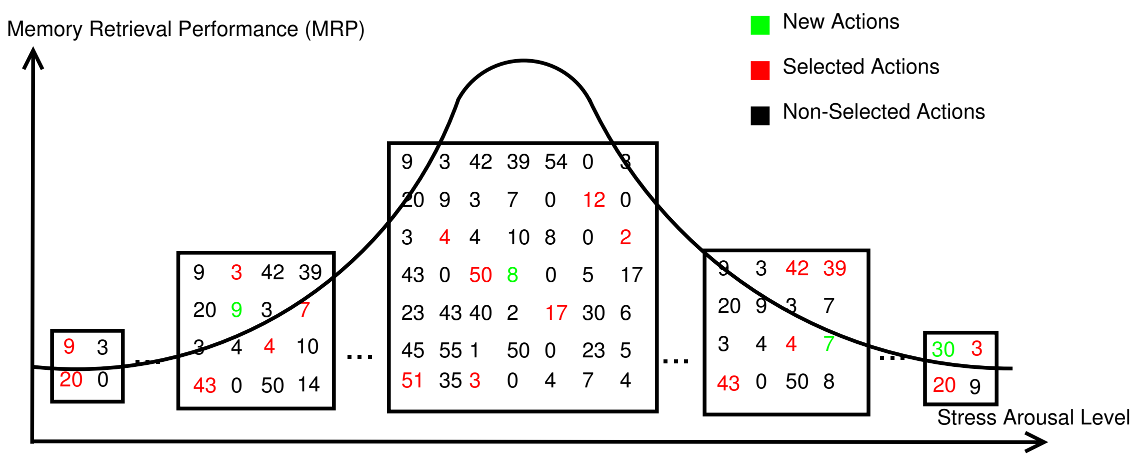


Figure 3.5: Illustration of *stressMemoryProcessing* Function Process.

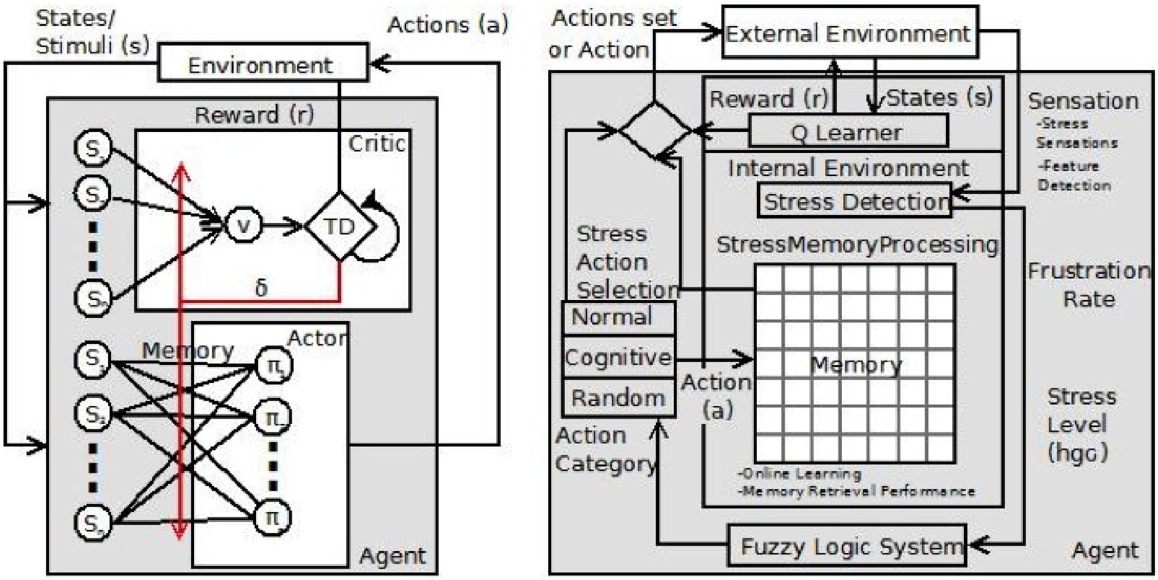


Figure 3.6: Comparison between the Actor Critic [12] (left) Framework and the Proposed SBMRP (right) Reinforcement Learning Framework.

Algorithm 3 stressMemoryProcessing

Function $stressMemoryProcessing$ ($agent$, $action$)
  $\sigma = 2$; //Define mrp standard deviation
  $\mu = 5$; //Define mrp mean
  $mrp = gaussmf(agent.h_{gc} \times 10, [\sigma\ \mu]) \times 7$;
  If $mrp < 1$ **Then**
    $mrp = 1$; //Set lower limit for mrp
  End If
  If $agent.action\_set$ still have non-selected actions **Then**
    //Select the first action from $action\_set$
    //Remove the first action from $action\_set$
  Else
    //Randomly choose row and column $coordinates$
    //Assign $action$ to $agent.memory$ at selected random $coordinates$
    //Randomly select uniqe set of $|mrp|$ total actions from $agent.memory$ for $agent.action\_set$
  End If
End Function

3.8 Experimental Settings

The proposed experiment environment was extended from Busoniu's Multi Agent Reinforcement Learning (MARL) Matlab toolbox [28]. The experimental environment is a agent restaurant (Figure 3.7). Subsequently, for the performance comparison the MARL toolbox is treated with the state-of-the-art reinforcement learning benchmark approaches. The computing machine used is a Windows 7, 64 bits operating system machine with Intel 3770 i7 CPU at 3.4GHz and 16GB of RAM PC.

The experimental execution settings are divided into two groups, i.e. the full trial and the reduced experimental settings. To understand the immediate results for the high processing requirement reinforcement learning approaches of ASFQ and FFQ, the reduced trial setting experiment is used for both the ASFQ and FFQ approaches.

On the other hand, the other proposed model's performance and stability are observed with a full trial experimental setting. The parameter setting for the reduced trial simulation environment is a maximum of $5,000$ steps per trial and for 30 trials. This simulation environment's parameter for full trial settings is set at 100 trials with maximum of $100,000$ steps per trial. For both reduced and full trial settings, five samples for experimental execution are required to compute the 95% confidence interval.

The agent's restaurant environment reinforcement learning parameters are configured as discount factor $\gamma = 0.95$, learning rate $\alpha = 0.2$, exploration probability $\epsilon = 0.333$ and eligibility trace decay rate $\lambda = 0.5$. The agent's restaurant environment is a wall-free 10×10 grid representation environment. The obstacle agent will pursue the agent that is closer to it except for a neutral obstacle agent class.

All the obstacle agents except those in the neutral class have the capability to stop the agent from mobility. The stopped agent cannot move to other grids and will remain in its original location until the agent gives the correct consecutive instructions to the obstacle agent. This stop capability is only possible within the eight grid areas of the agent nearest to the obstacle agent. For the hostile animal and hostile human class, four consecutive correct actions are needed from the agent to set it free from retention. On the other hand, eight consecutive correct actions are needed for the task assignment human class, the reason is the task assignment human class obstacle agent requires more detailed consecutive correct actions. For example, "what food to bring and to where venue and to who" are detailed consecutive instructions. In contrast, less detailed consecutive actions are needed to mitigate the hostile obstacle agent class, this is because in the actual situation of distress calling for help it will not need to be detailed to effectively mitigate the situation.

The feed forward neural network is assigned to the online ANN machine learning algorithm for this proposed SBMRP model in Algorithm 3.7. The mentioned online ANN machine learning is trained with back propagation Algorithm [140]. The parameter settings for the ANN are learning epochs of 10, 55 hidden nodes, and each input batch of 5 inputs with 32 binary features. Next, the 32 input binary features are the combination of 2 bits features for abstract class, 5 bits features for class and 15 bits features for concept of the obstacle agent. The setting of the obstacle abstract class, class and concept for the obstacle agent in the agent restaurant world are presented in Table 3.1.

Table 3.1: The *RestaurantWorldStressTable* representation for the obstacle agent in the simulated experiment environment.

Stress	Abstract Class	Class	Concept
3	Human	Hostile Human	Robber
3	Human	Hostile Human	Punk
3	Human	Hostile Human	Aggressive Boy
3	Human	Hostile Human	Gangster
3	Human	Hostile Human	Aggressive Man
2	Human	Task Assign Human	Manager
2	Human	Task Assign Human	Technician
2	Human	Task Assign Human	Owner
2	Human	Task Assign Human	Customer
2	Human	Task Assign Human	Waiter
1	Human	Neutral Human	Visitor
1	Human	Neutral Human	Cleaner
1	Human	Neutral Human	Boy
1	Human	Neutral Human	Girl
1	Human	Neutral Human	Policeman
3	Animal	Hostile Animal	Wild Dog
3	Animal	Hostile Animal	Aggressive Dog
3	Animal	Hostile Animal	Wild Cat
3	Animal	Hostile Animal	Aggressive Cat
3	Animal	Hostile Animal	Rat
1	Animal	Neutral Animal	Puppy Dog
1	Animal	Neutral Animal	Shih Tzu Dog
1	Animal	Neutral Animal	Chiwawa Dog
1	Animal	Neutral Animal	Persian Cat
1	Animal	Neutral Animal	Siamese Cat

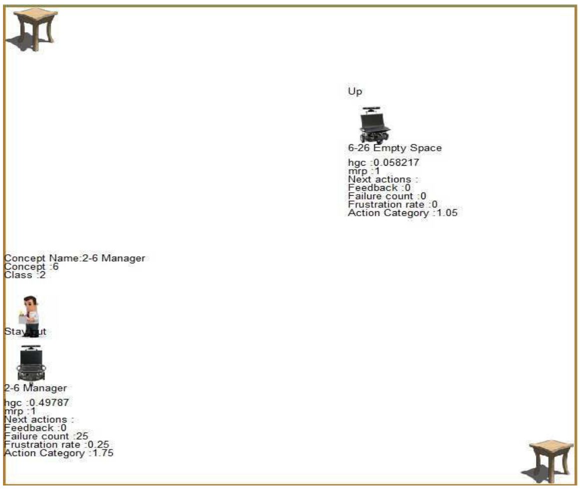


Figure 3.7: Agent Restaurant World Simulation Environment.

3.9 Experimental Results

The obtained experimental results are categorised into two parts, which are the reduced trial experiment parameter setting in Figure 3.8 and full trial experiment parameter setting in Figure 3.9.

3.10 Analysis of Results

The experimental results observed for the reduced trial experiment parameter setting in Figure 3.8 suggest that the proposed SBMRP model approach gives the best solution step convergence performance with the least number of steps needed for each trial in the simulation. Figure 3.8 shows a comparison of the SBMRP, SARSA, PlainQ, ASFQ and FFQ models for the agent restaurant world. The lines (dotted or straight lines) refer to the mean number of steps for 5 sample trial executions. The green, red, blue and grey areas are the 95% confidence intervals for the SBMRP, SARSA, PlainQ, ASFQ and FFQ experimental results respectively. The grey area is not visible because it is always at the peak of 5000 steps for all trials. For both SARSA and FFQ the confidence interval in the grey area is zero because of the $5,000$ steps per trial limit. Hence, other reinforcement learning approaches that are benchmarked in this chapter are not suitable for the stress-conditioned environment. The reason is the additional stress mitigation actions by the agent will cause its solution step convergence performance to decrease.

Figure 3.9 shows a comparison of the SARSA, PlainQ and SBMRP models for the agent restaurant world. The lines (dotted or straight lines) refer to the mean number

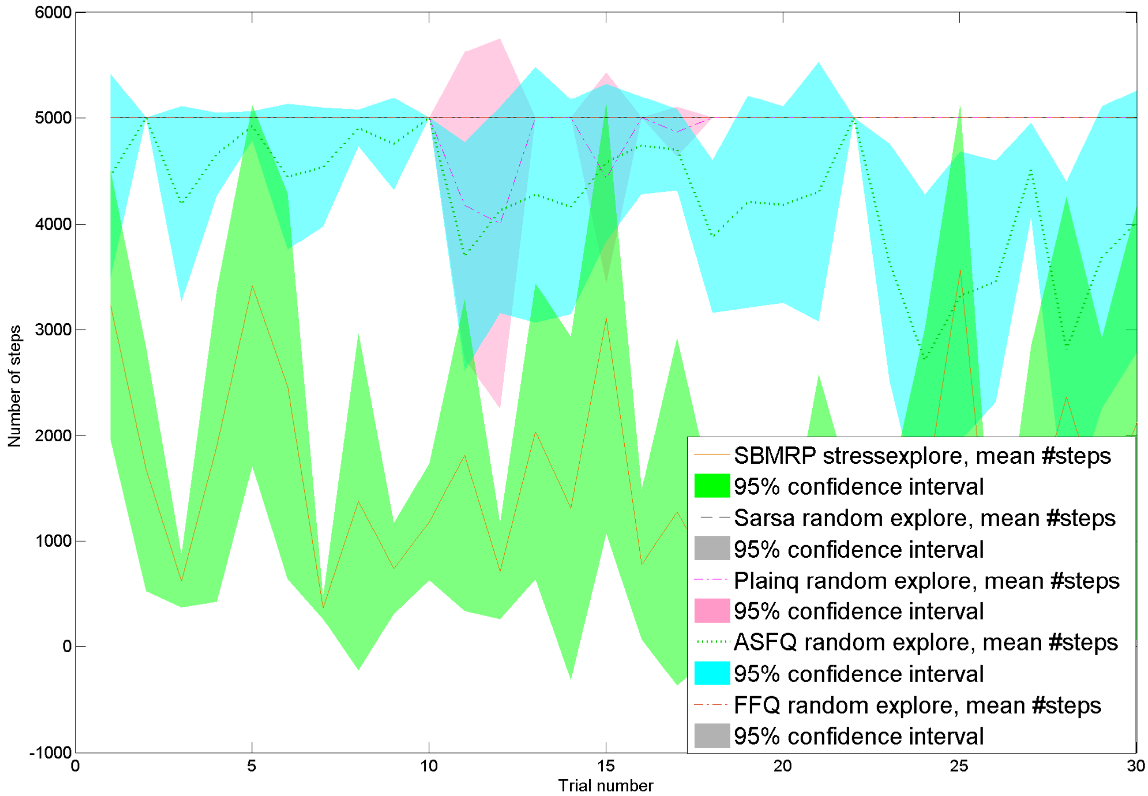


Figure 3.8: Partial Trial Experiment Parameter Setting with 5,000 Maximum Steps and 30 Trials for SBMRP, SARSA, PlainQ, ASFQ and FFQ Models.

of steps for five sample executions. The grey, red and green areas are the 95% confidence intervals for the SARSA, PlainQ and SBMRP experimental results. As shown in this figure the proposed SBMRP approach achieved the best performance stability with 100 of trials experimental settings, seen from the minimum variations in its confidence interval. It also maintained in horizontal slope steps per trial performance in the graph. It means the agent can have stable adaptation towards the obstacle agent.

The PlainQ benchmark approach underperformed regarding stability because of the high variations observed in its 95% confidence interval. The reason is that SARSA approach 95% confidence interval variations did not show much different when compared with the SBMRP approach, because of the maximum cap of 100,000 steps set per trial. Nevertheless, the number of steps per trial increased for the SARSA approach and it has the same positive slope behaviour as PlainQ.

In contrast, the number of steps per trial for the SBMRP approach maintained its horizontal slope throughout all the trials making it a much stable approach when compared with SARSA. The positive slope for SARSA and PlainQ may be caused by the limited adaptability of the models in the stress-simulated environment.

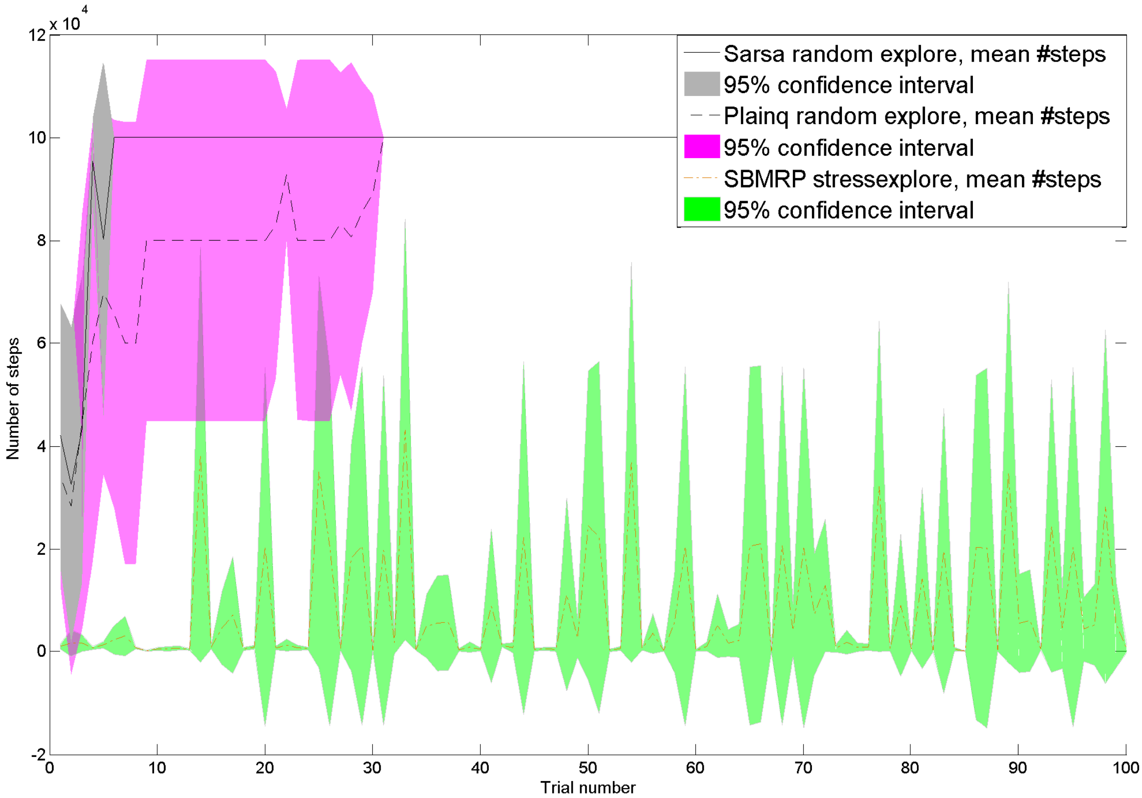


Figure 3.9: Full Trial Experiment Parameter Setting with 100, 000 Maximum Steps and 100 Trials for SARSA, PlainQ and SBMRP Models.

3.11 Contributions

The proposed SBMRP model has three main contributions:

1. The proposed SBMRP model can be applied to stress-simulated environment reinforcement learning to produce a reasonable efficient performance when compared with other approaches. Figure 3.8 shows the proposed SBMRP model requiring the lowest number of steps for each trial.

2. The proposed SBMRP model shows stability in its performance when compared with other reinforcement learning approaches. In Figure 3.9, the 95% confidence interval variation for the SBMRP model is the lowest green coloured area. The SBMRP approach also keeps its adaptation stability in the experimental result by exhibiting horizontal slope steps per trial behaviour. The horizontal slope steps per trial represents the learning agent stable adaptation toward obstacle agent.

3. Furthermore, the proposed SBMRP model design has successfully reduced its

action-state complexity. The reduction of action-state complexity in the proposed model refers to the generalisation of three action categories. Hence, certain actions can only be activated during a specific agent's stress state. The main reason is that the agent will consider smaller actions in the simulation. As an example, the agent may only consider five possible actions in *normalAction* category and will consider 55 possible actions only in different stress conditions; the action group selection changes to the *cognitiveAction* and *randomAction* categories.

3.12 Chapter Summary

In this chapter, a novel SBMRP intrinsically motivated reinforcement learning approach is proposed. The proposed model is inspired by the biological stress principles based on Yerkes and Dodson's [186] inverted-U-shape relationship stress arousal and working memory.

The proposed SBMRP model outperforms other benchmark approaches in a stress-simulated environment. Furthermore, the proposed method leads to optimal policy convergence and also regarding policy stability after its learning convergence has been achieved. On top of that, the proposed SBMRP model can handle larger domain's problem. The future work of the research is to explore the proposed model for multi-agent learning and knowledge transfer between different agents.

The stress perspective for reinforcement learning for the agent path optimisation is very limited concerning social support to the elderly. In this chapter, the agent only performs path optimisation that is fixed and limited in the context of the agent restaurant setting.

A more general human-robot interaction system is needed to support socially the elderly. The reason is that a human-robot communication requires large dimensional input and real-time processing beyond the reinforcement learning that the MDP model's capability can offers. The MDP model is not suitable for scaling in a high dimensional human-robot communication problem. In the next chapter, the agent's working memory is utilised and enhanced with optimisation algorithm for general human-robot interaction system to support the elderly. A novel general-purpose evolutionary algorithm will be proposed. The same proposed evolutionary algorithm is then used to improve the agent's working memory optimisation.

Chapter 4

Internal Representation in Working Memory

4.1 Introduction

This chapter further investigates research question 3 (RQ3) of subsection 1.7.3, "Can we improve the state of the art cognitive intelligence for robot partners by applying biological principles?". Specifically, we look into how to better address the robot partner's internal optimisation representation of its working memory with a biologically-inspired model. A robot partner's working memory needs dynamic optimisation because its intention influences the situation (section 1.8). The term *dynamic* refers to the optimisation tasks performed on the volatile working memory storage. The concept of dynamic working memory optimisation is also described as the *cognitive load* [165] (subsubsection 2.4.7.2) of an individual processing his or her working memory to solve a problem. For example, if a person is searching for his lost phone (intention), those searched areas should not be searched again by optimisation of (or updating) his working memory of these areas. Hence, the robot partner's working memory stored concepts will need to be optimised according to its current intention to perform its task with incremental improvement.

In the previous chapter (Chapter 3), reinforcement learning was proposed to update or optimise the robot partner's path navigation and feed-forward neural network classification to learn perception-action selection behaviours. However, these optimisation methods are not suitable for working memory-based optimisation in daily human-robot conversation. For example, in a human-robot discussion about the weather, the reinforcement learning and feed-forward neural network cannot process the strings in the weather dialogue. On the other hand, an evolution computation method can treat the stringed sentences as chromosome representations and the words in a sentence as genes represent genetic optimisation. Hence, in this chapter two novel evolution computation genetic optimisation methods are proposed. These computation methods would be integrated into the next chapter as the optimisation method for the robot partner's *cognitive load* [165] working memory processing.

Dynamic optimisation of the robot partner's working memory is needed because the robot partner's *heuristic mechanism* [134, 149, 176] (subsection 2.4.7) in a situation triggers new intention scenarios (section 1.8 for research overview). The heuristic technique is needed when the problem situation can no longer be optimised. Hence, a new intuition or intention will be created to mitigate the stressful situation. The new intuition creation mechanism (or free will or heuristic technique [149]) will be discussed in detail in Chapter 8. In sum, the robot partner's optimised working memory will contribute as a data source for the robot partner's heuristic technique to create its new intention. For example, if a robot partner is discussing a topic on sports with its user while the user is washing his clothes after lunch. Then, the robot partner's working memory will be filled or referenced with those concepts related to sports such as shoes, weather, scores as well as the concepts available while washing the clothes. The robot partner's working memory will optimise to store all concepts related to sports and topics discussed during lunch will be slowly overridden or updated. Subsequently, the robot partner construction of new dialogue will be based on the current concepts stored in its working memory. For example, "Please remember to *wash* your *shoes*." is the new dialogue generated in the middle of the human-robot conversation based on the working memory information during a sports conversation and an event involving washing of clothes. Thus, the robot partner's working memory dynamic optimisation is needed to supply the *relevant or optimised* concepts about a topic for its heuristic or new dialogue generation behaviour.

In evolution computation terms, the current intention is the evaluation function of the population. The robot partner's working memory can act as the *population* for the evolution computation optimisation algorithm to process on. As a result, an improved optimisation algorithm that is efficient and effective is needed to conduct real-time optimisation of the robot partner's working memory for its human-robot interactions. In this chapter, two novel EC's operators are proposed for general optimisation problems. Although they are not specifically designed for the robot partner's working memory optimisation only, it is reasonable to prove our proposed optimisation genetic operators performance in different domains as well. Hence, in this chapter we apply the two proposed genetic operators in commonly used fuzzy logic rules optimisation problems [21, 23, 125, 162, 168].

Much evolutionary computation (EC) [45] approaches are proposed to solve the NP-hard optimisation problems empirically. Even so, the genetic operators in these proposed EC models are yet to be fully exploited for optimisation improvements (the identified gaps). In other words, efficiency and effectiveness improvements of these EC genetic operators are needed for real-time human-robot interaction system. Furthermore, two novel genetic operators are proposed to address these gaps. The first proposed genetic operator is named *Dynamic Programming Gene Transfer (DPGT)* operator and the second proposed genetic operator is called *Average Edit Distance Bacterial Mutation (AEDBM)* operator. The main purpose of these proposed operators is to improve the proposed state-of-the-art EC method, which in this chapter is referred to as Bacterial Memetic Algorithm by Botzheim et al. [23].

Edit distance comparison that is based on *dynamic programming (DP)* [17] is integrated into the gene transfer operator in Bacterial Memetic Algorithm (BMA) [23]. Selected good genes are transferred between bacterium individuals in the DPGT approach by edit distance comparison before transferring the genes to other bacterium individuals.

Furthermore, the DPGT operator is tested with an artificial learning agent that is the ant's perception-action environment. The ant's perception-action environment problem is selected to prove its performance in other general optimisation problem domains such as fuzzy logic rules optimisation problems [21, 23, 125, 162, 168]. Initial experimental results indicated that the first DPGT approach outperformed the benchmark approach with improvements in training accuracy. Besides, the DPGT approach did not have any much impact on its training processing time. Thus, the proposed DPGT approach in this chapter will be utilised in later Chapters 5 and 7 on reactive control [26] to optimise the robot partner's working memory.

4.2 Overview

Evolutionary computation [45] approaches are very popular optimisation tools inspired from nature's evolution or adaptation. These adaptation features are then modelled into computational optimisation algorithms.

The EC strategy is used to model an artificial learning agent ant's perception-action problem. For this chapter, an artificial ant environment as a general fuzzy logic rules optimisation problem is used to test the proposed optimisation algorithm performance. For the artificial ant to survive in its environment, it is crucial that both its cognitive load computational time and perception-action learning errors remain minimum. As an example, when a learning ant agent senses a threat from its environment with its limited insect vision [93], the learning ant agent will need to respond to the condition with a correct action. The example of a correct action is to escape from the situation. Thus, it is important that the EC optimisation performance is improved without significantly taxing the overall perception-action learning time for the learning ant agent's survival.

Subsequently, a novel gene transfer operator called *Dynamic Programming Gene Transfer (DPGT)* is introduced. The DPGT operator utilises a fast string comparison method that is called *dynamic programming (DP)* [17] algorithm. DP is used to calculate the similarity between two individual's bacterial gene elements.

The term *memetic algorithm* in this chapter refers to a combination of local and global searches in optimisation approach. A local search approach example is the Levenberg-Marquardt (LM) [109]. For this chapter, a gene transfer operator of BMA [21] is improved for better optimisation performance. The BMA approach is proposed to solve fuzzy logic rules optimisation problems [21], fuzzy neural network optimisation problems [22] and path planning optimisation problem [24]. The proposed DPGT operator is applied to improve the BMA's existing gene transfer operator for fuzzy logic rules optimisation experiment [21].

Furthermore, the proposed DPGT operator is investigated with a learning agent ant's perception-action problem. The learning agent ant problem arising from the ant's limited vision ability [93] is utilised based on the assumption that its visual perception exists only in pixel resolution.

4.3 Motivation for Experiment

The proposed DPGT approach checks for the source and destination bacterium's gene elements differences with *Levenshtein Distance* or *Edit Distance* [99] calculation. Then the calculated result will determine whether to transfer the gene elements to another bacterium individual.

Hence, a *good gene transfer* takes place when a *variety* of gene elements are transferred to the destination bacterium. For the initial result in this chapter, a good gene transfer can improve the learning agent's overall optimisation performance. In contrast, a *bad gene transfer* is when *similar* gene elements are transferred to other bacterium individuals and then produce an overall bad optimisation performance. Bad gene transfer can be observed in the real world if a population conducts closely related breeding. This phenomenon is also known as *inbreeding depression* [79].

Algorithm 4 Bacterial Memetic Algorithm

procedure BMA
  Initial bacterial population
  $generation \leftarrow 0$
  while $generation \neq N_{gen}$ **do**
    AEDBM algorithm applied to each bacterial
    Local search for each baterium
    DPGT for the population
    $generation \leftarrow generation + 1$

Coincidentally, edit distance with dynamic programming has been introduced in gene similarity comparison in bioinformatics research [143]. Hence, it is intuitive that edit distance with dynamic programming is be integrated into the EC approach as well.

4.4 Objective of Experiment

The research aim of this chapter is to improve the overall EC optimisation performance without impacting its overall training time.

4.5 Bacterial Memetic Algorithm (BMA)

BMA is based on population stochastic optimisation memetics that combines both local and global searches (Algorithm 4). Hence, BMA is empirically proven to perform with a quasi-optimal solution. BMA performs the bacterial mutation and gene transfer in its global optimal search operators. The main reason of bacterial mutation is the optimisation of the bacterium's gene. In contrast, the Levenberg-Marquardt (LM) [109] method is applied in the BMA's local search technique in Botzheim et al. [21].

The BMA approach starts with a generation of an initial random population that consist of N_{bac} bacterial individuals (Algorithm 4). Then, BMA continues a repetition process until some generation N_{gen} conditions is fulfilled. In general, the BMA approach performs three different operators in the sequence that are the bacterial mutation, LM local search and gene transfer operators.

Firstly, the bacterial mutation operator initialises some N_{clones} clones of a bacterium. Then, these clones are subjected to select randomly a position to be assigned changes in their genes, except the chosen influencer clone. After the mutation process in the bacterial mutation operator is completed, all the clones are evaluated so that

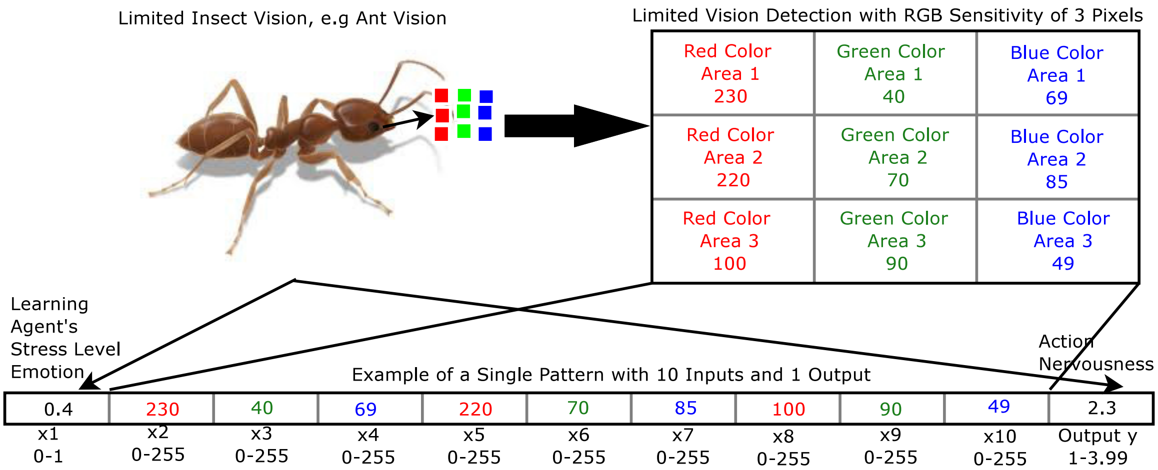


Figure 4.1: Perception-Action Problem of an Artificial Learning Agent Ant.

the one with the best fitness value will be selected from the other clones to be the influencer clone.

The length of the mutation segment L_{ms} parameter of the algorithm sets the total number of gene elements of a bacterial individual that need to be modified. Next, the LM algorithm [109] is applied for each bacterium until a certain number of iterations N_{iter} is made in the local search step. The τ and the initial bravery factor α are the two parameters that determine the loop termination condition.

The gene transfer operator is the final operator in the BMA approach that executes horizontal gene transfer. The horizontal gene transfer in the gene transfer operator refers to the duplication of good gene information to bad bacterium individuals. In other words, the bacterium population is separated into two groups after they are sorted according to their fitness values, i.e. the superior group and inferior group of the population.

Subsequently, the infection segment length L_{is} is a parameter that determines how many segments of gene should be transferred in each operation and N_{inf} is the number of infections imposed. These two settings are the BMA experiment's parameter settings.

4.6 Artificial Learning Agent Ant's Perception-Action Problem

In this section, the artificial learning agent ant's perception-action problem is discussed. A proposed method with increased optimisation effectiveness but without significantly impacting its processing time is a crucial contribution to this problem.

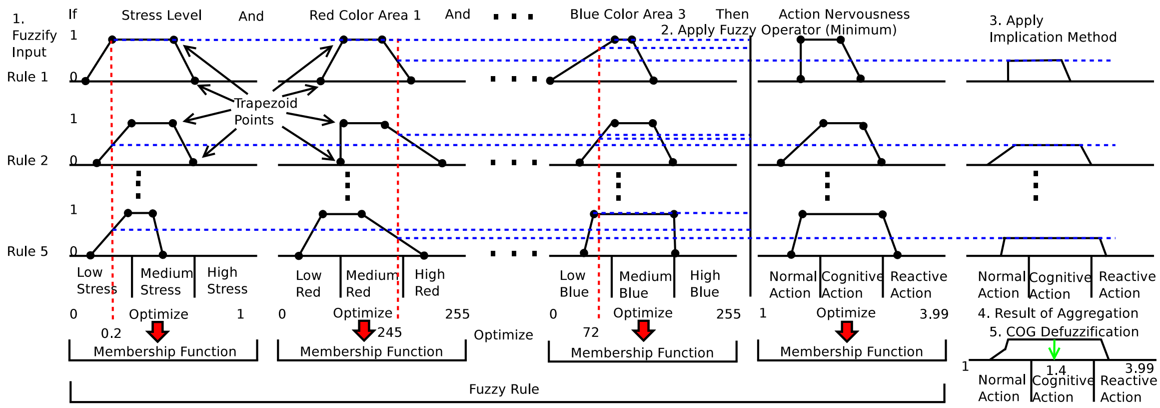


Figure 4.2: Fuzzy Inference System for an Artificial Learning Agent Ant's Perception-Action Problem.

The main reason is that the learning agent's survival relies on its correct and quick-learned actions. According to Pfeifer's definition of cognitive intelligence in definition 1.5.1 [135], survival is a crucial part of cognitive intelligence.

Figure 4.1 illustrates the learning agent ant's perception-action problem. The learning agent ant's visual perception is modelled as an aggregation of Red, Green and Blue (RGB) pixels. The learning agent ant's vision concept detection is defined as RGB pixels representation with 3×3 dimensions. This setting is inspired by the insect's limited vision [93].

Figure 4.2 shows the Mamdani [108] fuzzy inference system used to estimate the output of the fuzzy inference system of the artificial learning agent ant's perception-action problem. The Mamdani fuzzy inference system with the centre of gravity (COG) defuzzification is used to estimate the output. The learning agent's stress emotion is represented as real values between 0 and 1. The proposed EC method's bacterium's gene elements are modelled as the concatenation of the learning agent's stress emotion and learning agent ant's vision RGB pixels with integer values ranging between 0 and 255. The proposed DPGT operator in this chapter optimises the bacterium's gene elements with membership function having fuzzy rule extraction application in Botzheim et al. [21].

4.7 Dynamic Programming Gene Transfer (DPGT) Algorithm

The Bacterial Evolutionary Algorithm (BEA) approach was initially proposed by Nawa and Furuhashi [125]. The BEA approach implements the *gene transfer* oper-

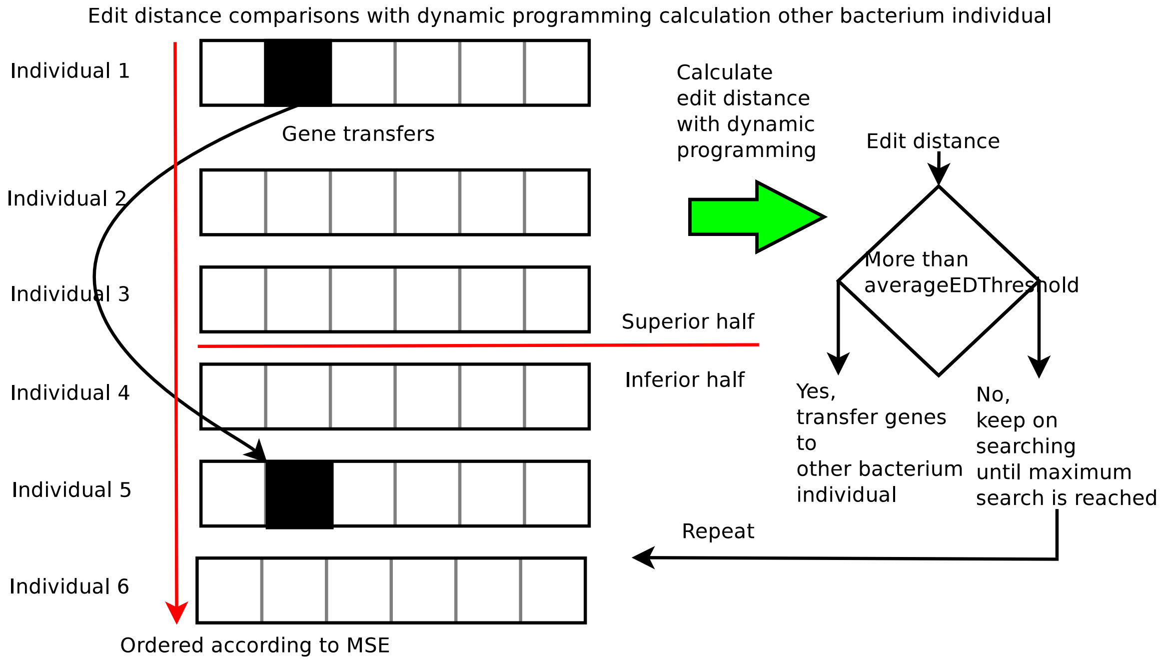


Figure 4.3: Illustration of the Dynamic Programming Gene Transfer (DPGT) Algorithm Process Flow Diagram.

ator in their algorithm. Next, a novel method named *Dynamic Programming Gene Transfer (DPGT)* is presented in Algorithm 5. The edit distance with dynamic programming calculation [17] is used to estimate similarity between source and destination of the bacterium's gene elements.

The proposed DPGT operator (Figure 4.3) conducts edit distance gene similarity comparisons before transferring genes from a superior to an inferior bacterium individual's gene elements. When the calculated edit distance value is larger than the computed average edit distance threshold (*averageEDThreshold*), only then the source bacterium's gene elements are selected to be transferred to the destination bacterium individual's gene. The transfer is only valid within the N_{search} number of similarity search counts for the similarity comparison.

Regarding edit distance calculation with dynamic programming, the real numbers in bacterium's gene elements are parsed into a string of characters with string based decimal point precision. For example, an edit distance comparison for similarity between two pairs of real values (4.53, 0.12) and (2.963, 0.1) are parsed into a string of characters of (453012) and (296301). On the other hand, the perspective of Hamming distance [68] calculation for the example is 4. Thus, Hamming distance had failed to measure similarities between source and destination bacterial individual's gene. In contrast, for the proposed method the minimum edit distance calculated is 2 which

Algorithm 5 Dynamic Programming Gene Transfer

```
procedure DPGT
    editDistanceCount ← 0
    editDistanceSum ← 0
    for q:=1,2 ... N_inf do
        Order Population into half as Superior (Source) and Inferior (Destination)
        Random Source Bacterium
        Random Destination Bacterium
        for r:=1,2 ... L_is do
            assigned ← False
            searchCount ← 0
            while Not assigned And searchCount < N_search do
                Random Select Source Bacterium Elements
                Random Select Destination Bacterium Elements
                Concatenate All Selected Source Bacterium Elements to String a
                Concatenate All Selected Destination Bacterium Elements to String b
                d_m,n ← minEditDistanceCalc(a, b)
                editDistanceCount ← editDistanceCount + 1
                editDistanceSum ← editDistanceSum + d_m,n
                averageEDThreshold ← editDistanceSum/editDistanceCount
                if d_m,n ≥ averageEDThreshold then
                    Assign Source Bacterium Elements to Destination Elements
                    assigned ← True
                searchCount ← searchCount + 1
```

is more appropriate to identify the suitability to transfer the gene to the destination bacterium individual. When the source and destination bacterium's gene elements are almost similar, it is crucial to stop the gene transfer to gain good optimisation result according to the analogy of inbreeding depression [79]. Therefore, the overall optimisation performance can be improved by minimising the bad gene transfers. Bad gene transfer refers to similar gene transfer between the source and destination bacterium individual's gene elements.

The proposed approach then calculates the edit distance with the dynamic programming [17] algorithm which is a very efficient method. As a result, the imposed additional gene similarity comparison does not cause significant processing cost to the overall processing time. The dynamic programming [17] algorithm is known to be efficient because it has the trade memory space with time property.

For this chapter, the proposed method improves the BMA's gene transfer operator step (Algorithm 4 in step 7) with the proposed DPGT operator and is implemented in [21] fuzzy rules optimisation problem.

Table 4.1: Parameter setting for the proposed algorithm

N_{gen}	N_{bac}	N_{clones}	L_{ms}	N_{inf}	L_{is}	N_{iter}	τ	α
20	3	4	1	5	1	5	0.0001	1

Let's defines $d_{i,j}$ as the edit distance matrix with dimensions $i \times j$ between string a and string b. Next, the cost function is denoted as c. The cost values for delete, insert and substitution are all the same with $c_{del,ins,sub} = 1$. Furthermore, *minEditDistanceCalc* function in Algorithm 5 executes the following steps: First, it initialises the first row and column with Equations 4.1 and 4.2. Subsequently, it fills up all the remaining empty cells in the $d_{i,j}$ matrix with Equation (4.3).

$$d_{i,0} = \sum_{k=1}^{i} c_{del}, \quad for\, 1 \leq i \leq m \tag{4.1}$$

$$d_{0,j} = \sum_{k=1}^{j} c_{ins}, \quad for\, 1 \leq j \leq n \tag{4.2}$$

For $1 \leq i \leq m$, $1 \leq j \leq n$:

$$d_{i,j} = \begin{cases} d_{i-1,j-1} & \text{if } a_j = b_i, \\ \min \begin{cases} d_{i-1,j} + c_{del} \\ d_{i,j-1} + c_{ins} \\ d_{i-1,j-1} + c_{sub} \end{cases} & \text{otherwise.} \end{cases} \tag{4.3}$$

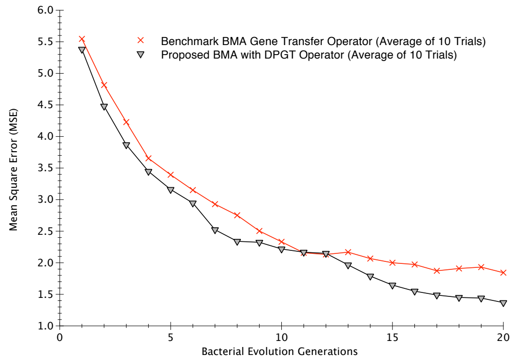
4.8 DPGT Experimental Settings

The experimental hardware setting is a MacBook Pro machine with 2.8 GHz Intel Core i7 processor with 16GB 1600 MHz DDR3 RAM. The software setting is Mac OS X 10.9.4 and the proposed approach is implemented in C++ application environment.

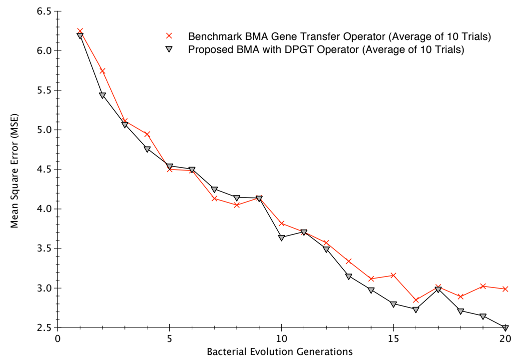
The number of input patterns is set at 50 for both training and test dataset and the total number of input features X is set at 10. Fuzzy rules number N_{fuz} is configured to 5. Then, maximum search count N_{search} is 5 and string decimal point precision is configured to 2 decimal points. The experimental parameter settings are listed in Table 4.1. Finally, the infection unit and mutation unit are set at membership function.

Table 4.2: Comparison

Experiment	GT	DPGT	Difference
Best MSE based on the average of 10 trials	1.843	1.369	34.62%
Population average MSE based on the average of 10 trials	2.988	2.502	19.42%
Best trial's best bacterium's MSE	1.460	1.133	28.86%
Best trial's population average MSE	2.425	1.924	26.04%



(a) Experimental result on test dataset based on best bacterium MSE.



(b) Experimental result on test dataset based on population average MSE.

Figure 4.4: Experimental results

4.9 DPGT Experimental Results

Figure 4.4a shows the experimental results for the *best* bacterium performed under Mean Square Error (MSE). Figure 4.4b illustrates the experimental data for *population average* bacterium performance regarding MSE. These two experimental MSE values were computed based on an average of 10 sample trials.

4.10 DPGT Result Analysis

The experimental settings are designed for comparison between the proposed DPGT approach and benchmark approach. In short, this chapter's proposed DPGT approach achieved overall lower Mean Square Error (MSE) for both the best bacterium and the population average (Figures 4.4a and 4.4b). The proposed DPGT approach on best bacterium achieved overall lower MSE in earlier generations than the benchmark; in short the proposed DPGT approach can converge faster (Figure 4.4a).

In conclusion, good gene transfer between bacterial individuals contributes to optimisation of performance gain. The DPGT approach enables the good gene transfers by reducing the inbreeding depression [79] effects. Table 4.2 gives a comparison of the experimental results from the original GT benchmark approach and the proposed DPGT approach. Besides, the benchmark approach's average computational time based on 10 trials is 39.1 seconds while that of the proposed DPGT approach is 41.7 seconds. Hence, the proposed DPGT approach only needed an additional 6.65% computation training time over the benchmark GT approach. Hence, the proposed DPGT approach has reasonable additional processing time over the benchmark approach. The reason is that Algorithm 5 has the time complexity of $O(N_{bac} \times log(N_{bac}) \times N_{inf} \times L_{is} \times |a| \times |b| \times N_{search})$. Meanwhile, the benchmark gene transfer operator's time complexity is $O(N_{bac} \times log(N_{bac}) \times N_{inf} \times L_{is})$.

However, the limitation of the DPGT approach is that the string decimal point precision parameter currently has to be manually configured according to different problems.

4.11 DPGT Contributions

The following items are the contributions in this chapter:

1. The proposed DPGT approach has achieved overall best performance MSE with an average of 10 sample trials when it is compared with the benchmark approach.
2. The proposed DPGT approach can converge faster with the mean of 10 sample trials in early bacterial evolution generations when it is compared with the benchmark approach.
3. The average execution time of the 10 sample trials for the proposed DPGT approach needs minimum additional processing time over the reference method. As a result, the proposed DPGT approach does not have a significant impact on its training time.

4.12 Average Edit Distance Bacterial Mutation (AEDBM) Algorithm

The proposed Average Edit Distance Bacterial Mutation (AEDBM) algorithm in this section has been applied to the robot partner's working memory dynamic optimisation for elderly people support system [169, 170]. The robot partner's working memory dynamic optimisation is used in the scenario where the situation (working memory) is optimised toward the intention. The proposed AEDBM approach is the second gene operator enhancement to the original BMA approach by Botzheim et al. [21].

It is important to have efficient working memory dynamic optimisation for real-time robot partner application. The reason is that human-robot interactions require a real-time response for higher user acceptance of the proposed robot partner solution. In this section, the proposed AEDBM optimisation approach is applied to general fuzzy rules optimisation problems. It is to show that the proposed method can be applied to different problem domains but still show its optimisation efficiency and effectiveness in general optimisation problems.

To gain better optimisation effectiveness performance, the proposed AEDBM algorithm reduces the ineffective bacterial mutation by applying edit distance gene similarity comparisons of bacterium individual's gene elements with other clones' gene elements before mutating them to other clones.

Let's define a variable called *average edit distance*, $average_{ED}$ that contains the mean edit distance value of all the clones. The $average_{ED}$ variable determines the good gene transfer condition to other bacterial clones. When the average edit distance value of all the clones' $average_{ED}$ is equal or larger than the $EDAvg$ edit distance threshold on step 24th in Algorithm 6, then it signals a major gene difference between the best bacterium and all its clones for executing good gene mutation. Figure 4.5 illustrates the AEDBM algorithm's working where the bacterium individual gene elements are mutated to others clones.

Steps 9 and 17 in Algorithm 6 execute a loop from the second clone until the $N_c + 1$ clone. The reason that the loop starts from the second clone is because the first clone is the best bacterium individual and it is not mutated. Consequently, the first bacterium individual's gene elements will be mutated to all the other clones.

Let L_{ms} be defined as the mutation segment length, then the number of bacterial as clones N_c, Boolean variable to toggle the bacterial mutation process as *assigned*. Then, the variable $count_{search}$ is to keep track of the total search count; the maximum search depth is defined as max_{search} for AEDBM and $total_{ED}$ is the integer variable for recording aggregated edit distance from all the clones. Let's denote a as the concatenated string for the best bacterial elements and b as the concatenated string of a clones' bacterial elements.

The edit distance is computed based on Algorithm 7. Edit distance algorithm starts from Equations 4.1 and 4.2 that initiate values for the first row and column of

Algorithm 6 Average Edit Distance Bacterial Mutation

procedure AEDBM
    $EDCnt \leftarrow 0$
    $EDSum \leftarrow 0$
    $EDAvg \leftarrow 0$
    Create clones
    Random mutation order
    for $l = 1, 2 \ldots N_{rules} \times (N_{input} + 1)/L_{ms}$ **do**
        for $h = 1, 2 \ldots L_{ms}$ **do**
            for $m = 2, 3 \ldots N_c + 1$ **do**
                $assigned \leftarrow False$
                $count_{search} \leftarrow 0$
                while $Not\ assigned\ And\ count_{search} < max_{search}$ **do**
                    Select bacterial elements randomly
                    Order the breakpoints
                    Concatenate mutating elements as a
                    $total_{ED} \leftarrow 0$
                    for $n = 2, 3 \ldots N_c + 1$ **do**
                        Concatenate nth clone as b
                        $total_{ED} \leftarrow total_{ED} + editDistance(a, b)$
                    $average_{ED} \leftarrow total_{ED}/N_c$
                    $EDCnt \leftarrow EDCnt + 1$
                    $EDSum \leftarrow EDSum + average_{ED}$
                    $EDAvg \leftarrow EDSum/EDCnt$
                    if $average_{ED} \geq EDAvg$ **then**
                        Assign selected bacterial elements
                        $assigned \leftarrow True$
                    $count_{search} \leftarrow count_{search} + 1$
        for $k = 1, 2 \ldots N_c + 1$ **do**
            Evaluate the kth clone
        Selection of the best clone
        Best clone transfers the mutated part to other clones
    Use the best clone as new bacterium

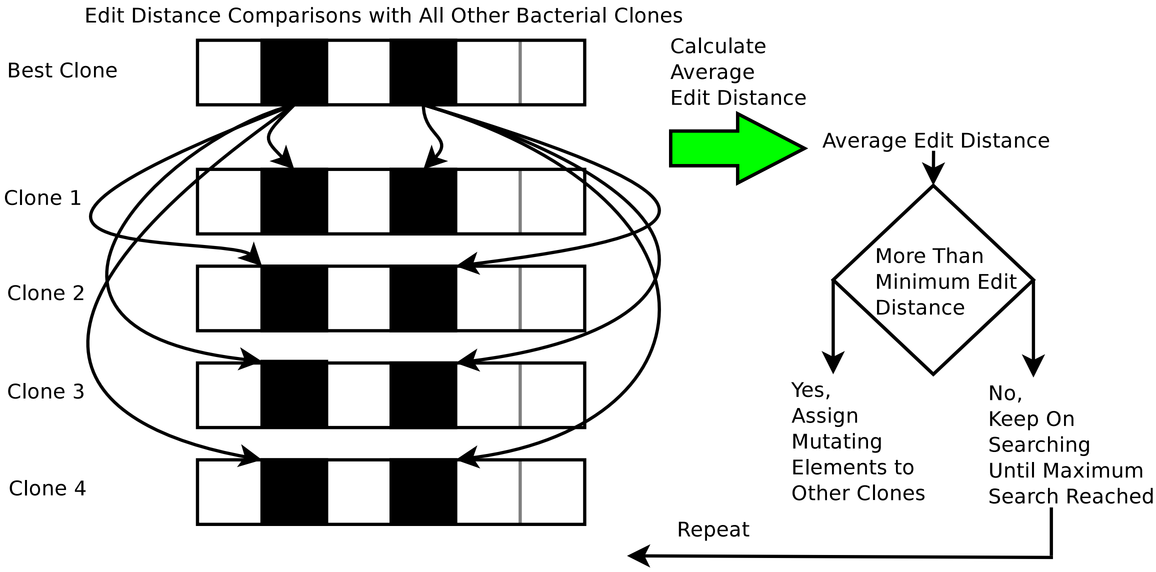


Figure 4.5: The AEDBM Algorithm Process Flow Diagram.

the matrix table d.

Equation 4.3 is the step that assigns the remaining empty value of the matrix table d with values. For every step, the Levenstein distance algorithm [99] compares the previous cell column or row column to assign the value for the selected cell value (see Equation 4.3 and Algorithm 7 in step 17). The costs for delete, insert and substitution have the same value of 1, where $c_{del} = c_{ins} = c_{sub} = 1$. The edit distance computes the minimum edit distance between two strings as explained by Levenstein's paper [99].

4.13 AEDBM Experimental Settings

In this section, the commonly tested dataset for fuzzy logic system analysis is utilised [21, 23, 125, 162] for the proposed AEDBM algorithm experiments. The proposed AEDBM algorithm can be applied following the general optimisation datasets as well as the robot partner's working memory optimisation in Chapters 5 and 7. The following subsections are the explanations for the datasets:

4.13.1 Generic Function of Six Dimensions

A six-dimension non-linear function generated the generic function for six-dimension datasets. It is called Six-Dimension Generic Function (6DIMS). Equation 4.4 is the generic nonlinear function for the six-dimension dataset generation. 6DIMS dataset

Algorithm 7 Edit Distance Calculation

procedure EDITDISTANCE(a, b)
    Declare i as length of string a
    Declare j as length of string b
    Declare integer variable $cost \leftarrow 0$
    //Define d as matrix of $i+1$ rows and $j+1$ columns
    Declare $d[0 \ldots i, 0 \ldots j]$
    for $m = 0 \ldots i$ **do**
        $d[m, 0] \leftarrow m$
    for $n = 0 \ldots j$ **do**
        $d[0, n] \leftarrow n$
    for $m = 1 \ldots i$ **do**
        for $n = 1 \ldots j$ **do**
            if $a[m] = b[n]$ **then**
                $cost \leftarrow 0$
            else
                $cost \leftarrow c_{sub}$
            $d[m, n] \leftarrow minimum(d[m-1, n] + c_{del}, d[m, n-1] + c_{ins}, d[m-1, n-1] + cost)$
    Return $d[i, j]$

is used in these works [21, 23, 125].

$$y = x_1 + x_2^{0.5} + x_3 x_4 + 2e^{2(x_5 - x6)} \tag{4.4}$$

4.13.2 Agricultural Data

The Agricultural Data (AGRI) records agriculture information on the properties of soil and its yield of maize [21]. In this dataset, it has 6-soil characteristics recorded. This dataset is for an efficient productivity plan to distribute fertilisers and other chemicals according to the actual soil conditions.

Regards to reduce the cost of actual physical measurements, the AGRI dataset is utilised to capture the distribution of fuzzy rules that can model the infrequent measured real data, so that it can reduce the actual measurement tasks to reduce the measurement cost.

4.13.3 Human Operation at a Chemical Plant Data

A five-dimensional human operation problem captured at a chemical plant data (HOCP) is used to model the operator's operation control of a chemical factory.

The full details of the HOCP dataset are described in the work of Sugeno and Yasukawa [162].

4.13.4 Concept-Action Mapping Data

Concept-Action Mapping (CAM) is a dataset for ant learning agent [168]. This dataset was discussed in section 4.6 on DPGT's dataset setting.

The AEDBM experimental settings have been categorised into two categories, hardware-software settings and parameter settings.

4.14 AEDBM Hardware and Software Settings

The experimental computation hardware is a MacBook Air with Intel Core 2 Duo 1.86 GHz processor with 4 GB 1067 MHz DDR3 RAM operated on Mac OS X 10.9.3 operating system. C++ application environment is used to execute AEDBM algorithm. Furthermore, AEDBM algorithm is an improvement of Botzheim et al.'s [21] implementation.

The experiment is performed will the proposed AEDBM algorithm simulation on the training datasets defined in section 4.13. Then, the output of the training datasets trained by the AEDBM algorithm will be used to evaluate the testing dataset with Mean Square Error (MSE).

4.15 AEDBM Parameter Settings

Table 4.3 describes the parameter settings for the 6DIMS, AGRI and HOCP datasets. In short, the number of inputs denoted as N_{input} for 6DIMS is 6, for AGRI is 6, for HOCP is 5 and for CAM is 10. Next, the total number of training patterns for 6DIMS is 200, for AGRI is 40, for HOCP is 50 and for CAM is 50. Furthermore, the total number of test patterns for 6DIMS is 200, for AGRI is 23, for HOCP is 20 and for CAM is 50.

Table 4.4 is designed for the CAM dataset's parameter setting. The reason why a new set of parameter settings is required because the defined decimal point precision $N_{precision}$ is data dependent.

The defined mutation unit scope $scope_{AEDBM}$ is the *Membership Function (MF)* and its gene transfer infection unit scope $scope_{GT}$ is set at *MF* too. The maximum search is denoted as max_{search}, the total number of repeated experiment simulation as $repeat$ and the bacterial mutation precision as $N_{precision}$.

Table 4.3: Parameter Settings for the 6DIMS, AGRI and HOCP Datasets

N_{rules}	N_{gen}	$N_{bacterial}$	N_c	L_{ms}
5	20	8	8	1

N_{in}	L_{is}	N_{iter}	τ	α
3	1	3	0.0001	1

max_{search}	$N_{precision}$	$scope_{GT}$	$scope_{AEDBM}$	$repeat$
10	3	MF	MF	10

Table 4.4: Parameter Settings for the CAM Dataset

N_{rules}	N_{gen}	$N_{bacterial}$	N_c	L_{ms}
5	20	5	10	1

N_{in}	L_{is}	N_{iter}	τ	α
3	1	3	0.0001	1

max_{search}	$N_{precision}$	$scope_{GT}$	$scope_{AEDBM}$	$repeat$
8	2	MF	MF	10

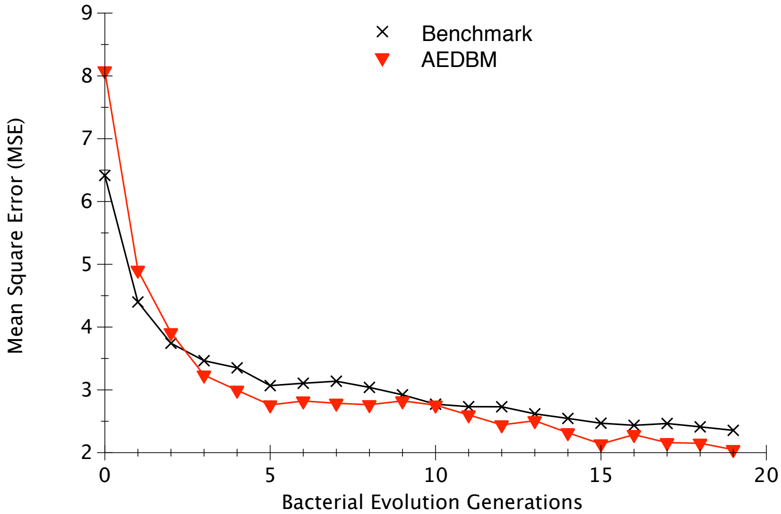


Figure 4.6: Comparison Between the Benchmark BMA and AEDBM Approaches in the Six-Dimension Generic Function (6DIMS) Test Dataset with Average MSE Results of 10 Averaged Sample Simulations and Best Bacterium's MSE Results.

Table 4.5: Overall Best Bacterium's MSE Differences between the Benchmark and the AEDBM Approaches According to Different Experimental Dataset Settings.

Dataset	6DIMS	AGRI	HOCP	CAM
Benchmark	2.36	2.08	9145297.58	2.52
AEDBM	2.05	2.17	2124053.91	1.14
% Changes	−13.14%	+4.33%	−76.77%	−54.76%

The $N_{precision}$ parameter is used to regulate the dataset dependent string comparison length in edit distance calculation. Then, the total numbers of *repeat* experiment simulations are utilised to compute average results of the experiment because the reason is that the AEDBM algorithm is a stochastic search optimisation.

4.16 Analysis of AEDBM Results

The proposed AEDBM algorithm is used to compare with the benchmark approach [21] to produce the experiment results. Figures 4.6–4.13 are the average results for the 10-repeated experimental simulations. Table 4.7 presents the total computation time differences between the benchmark and proposed AEDBM algorithm.

Figures 4.6–4.13, show that the proposed AEDBM approach can outperform the benchmark's approach at the final bacterial evolution generation for all its test datasets except for the AGRI best test dataset regarding average and best MSE performance.

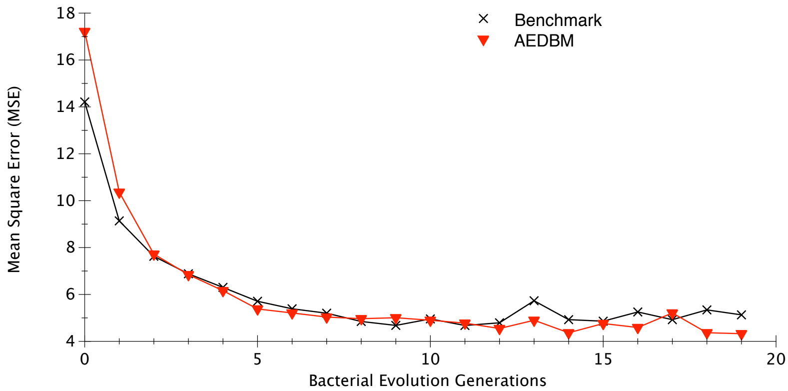


Figure 4.7: Comparison Between the Benchmark BMA and AEDBM Approaches in the Six-Dimension Generic Function (6DIMS) Test Dataset with Average MSE Results of 10 Averaged Sample Simulations and Average Bacterium's MSE Results.

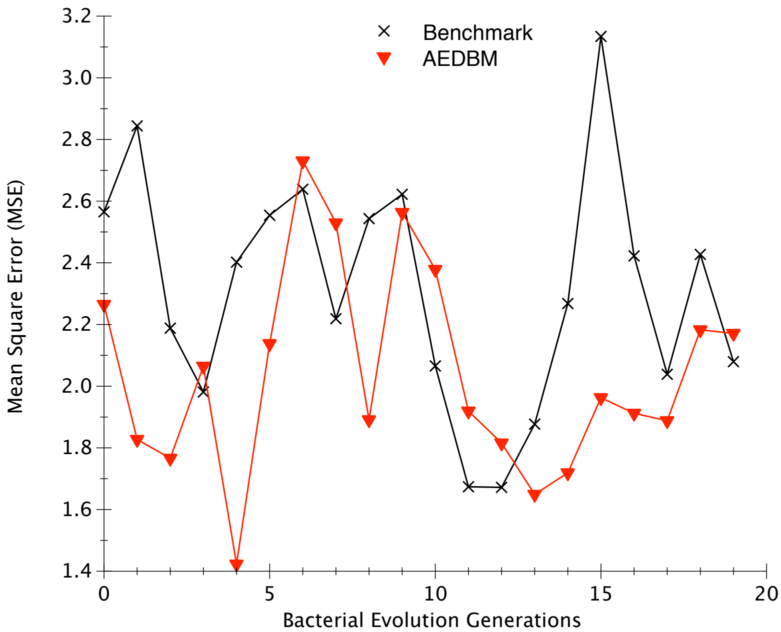


Figure 4.8: Comparison Between the Benchmark BMA and AEDBM Approaches in the Agricultural Data (AGRI) Test Dataset with the Average MSE Results of 10 Averaged Sample Simulations and Best Bacterium's MSE Results.

Table 4.6: Overall Average Bacterium's MSE Differences between the Benchmark and the AEDBM Approaches According to Different Experimental Datasets Settings.

Dataset	6DIMS	AGRI	HOCP	CAM
Benchmark	5.13	7.69	24909800.27	4.52
AEDBM	4.33	5.88	24217550.99	2.68
% Changes	−15.59%	−23.54%	−2.78%	−40.71

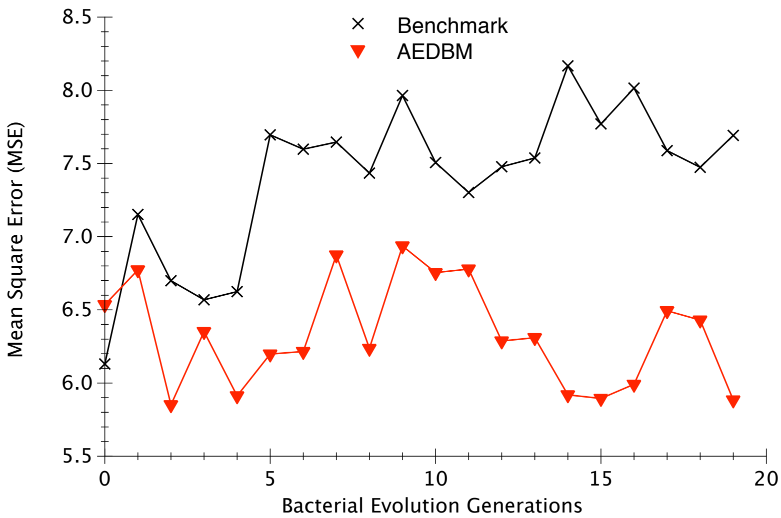


Figure 4.9: Comparison Between the Benchmark BMA and AEDBM Approaches in the Agricultural Data (AGRI) Test Dataset with Average MSE Results of 10 Averaged Sample Simulations and Average Bacterium's MSE Results.

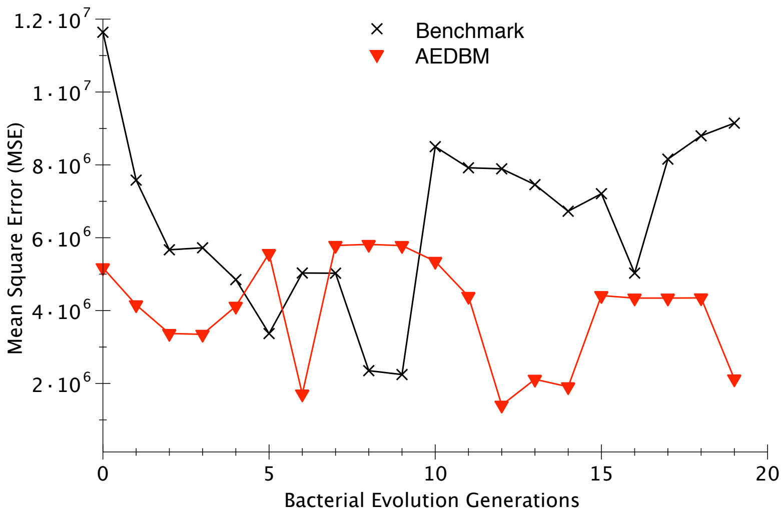


Figure 4.10: Comparison Between the Benchmark BMA and AEDBM Approaches in Human Operation in the Chemical Plant (HOCP) Test Dataset with Average MSE Results of 10 Averaged Sample Simulations and Best Bacterium's MSE Results.

Table 4.7: Processing Time Differences between the Benchmark and AEDBM Approaches According to Different Experimental Datasets Settings.

Dataset	6DIMS	AGRI	HOCP	CAM
Benchmark	69.4s	26.4s	17.8s	44.1s
AEDBM	72.7s	31.3s	26.2s	51.5s
% Changes	+4.76%	+18.56%	+47.19%	+16.78%

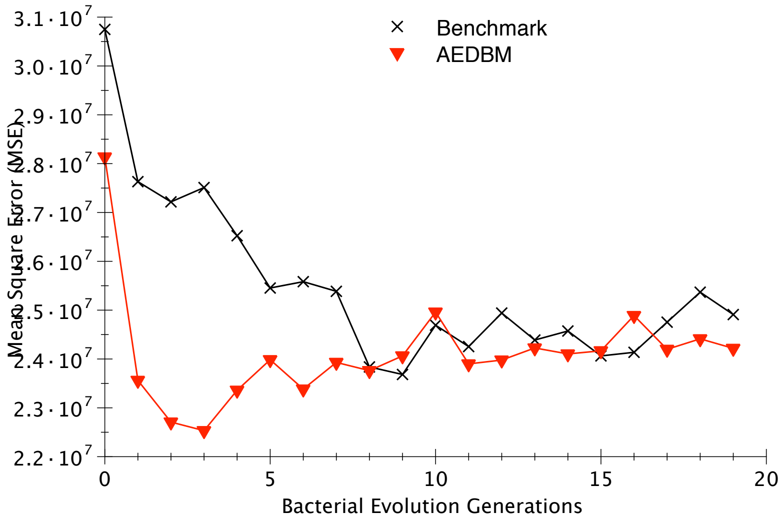


Figure 4.11: Comparison Between the Benchmark BMA and AEDBM Approaches in Human Operation in the Chemical Plant (HOCP) Test Dataset with Average MSE Results of 10 Averaged Sample Simulations and Average Bacterium's MSE Results.

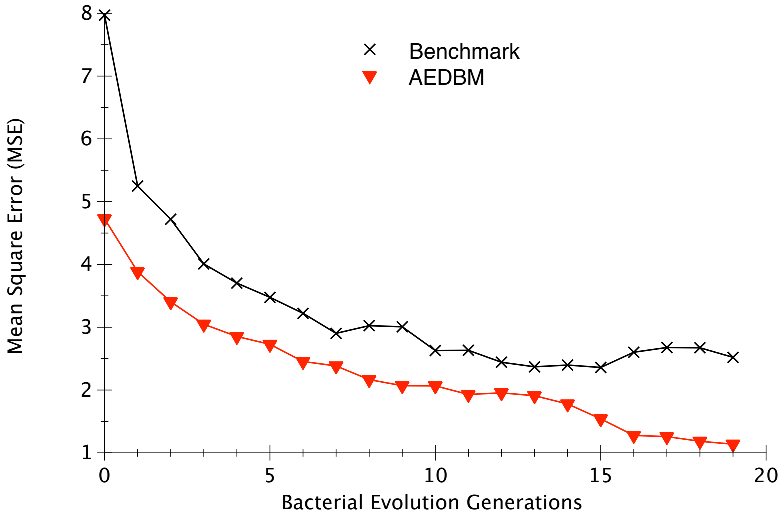


Figure 4.12: Comparison Between the Benchmark BMA and AEDBM Approaches in the Concept-Action Mapping (CAM) Test Dataset with Average MSE Results of 10 Averaged Sample Simulations and Best Bacterium's MSE Results.

The Figures 4.6–4.13 also show that the proposed AEDBM approach has overall better performance concerning early optimisation lead with its best and average MSE performance metrics at the initial five bacterial evolution generations. These conditions hold true for all the test datasets except for the HOCP best test dataset.

Under these experimental performance observations, it is concluded that these phenomena are the results of the reduction of bad gene mutation elements. Hence,

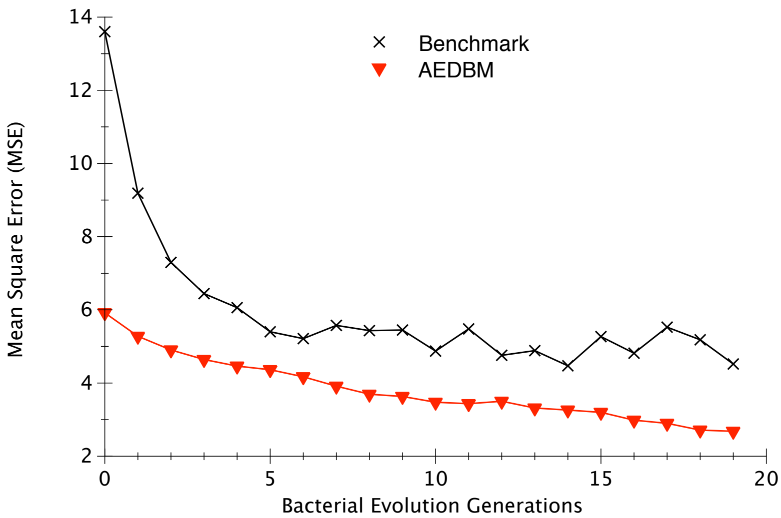


Figure 4.13: Comparison Between the Benchmark BMA and AEDBM Approaches in the Concept-Action Mapping (CAM) Test Dataset with Average MSE Results of 10 Averaged Sample Simulations and Average Bacterium's MSE Results.

the proposed AEDBM approach can outperform the overall optimisation performance when compared with the benchmark approach. For all the experimental datasets, the overall best and average bacterium MSE percentage improvements are -35.09% and -20.66% respectively Tables 4.5 and 4.6 give the best and average MSE results and percentage comparisons between the benchmark and AEDBM approaches respectively.

Under these observations, it is concluded for the proposed AEDBM approach that its additional processing time needed is not significant when compared with the benchmark approach. The total average additional processing time cost required for the AEDBM approach for all its experiment datasets is $+21.82\%$ as shown in Table 4.7 for time comparison. Hence, extra time needed for the AEDBM approach is not significant when compared with the benchmark approach.

Time-complexity analysis for the AEDBM approach's big-O notation is $O(N_{bacterial} \times N_c \times L_{ms} \times |a| \times |b| \times max_{search})$. On the other hand, the time-complexity for the original bacterial mutation operator is $O(N_{bacterial} \times N_c \times L_{ms})$. As a result, the proposed AEDBM approach can perform but still retains its low processing time requirement.

4.17 AEDBM Contributions

The proposed AEDBM approach has three main identified contributions:

1. The proposed AEDBM approach can outperform the benchmark approach at the end of the bacterial evolution generations.

2. The proposed AEDBM approach can converge faster than the reference method at the beginning of the bacterial evolution generations.

3. The overall additional processing cost needed for the proposed AEDBM approach is not significant when compared with the benchmark approach.

4.18 Chapter Summary

Two different gene operators, the DPGT [168] and AEDBM [167], are introduced in this chapter. These gene operators can outperform the benchmark approach in the optimisation of many commonly used fuzzy logic rules problems. These two proposed approaches give best results in overall optimisation MSE performance when compared with the reference method. Furthermore, they show early solution convergence at the beginning of the bacterial evolution generations. Also, these proposed approaches can perform without much additional processing time needed.

The both AEDBM [167] and DPGT [168] algorithms are derived from the bacterial mutation and gene transfer operators in BMA [21] respectively. The proposed enhancement on these two operators is the similarity comparison between chromosomes before gene transfer and bacterial mutation of the chromosomes. The functional difference between these two operators are described as below:

1. The AEDBM operator is best suited to problems that require more exploratory solution searching in chromosomes. Then, this operator is less focus on exploitation of best chromosomes to the rest of the population.

2. The DPGT operator will perform well with problems that require less exploratory solution searching in chromosomes. Then, this operator is more focus on exploitation of best chromosomes to the rest of the population.

Chapter 5

Optimal Information Processing at Working Memory

5.1 Overview

This chapter investigates research question 3 (RQ3) in subsection 1.7.3, "Can we improve the cognitive intelligence for robot partners by applying biological principles?". Specifically, we evaluating the robot partner's working memory optimisation with human-robot game interaction pilot test.

Robot partner social support applications such as game interactions with the elderly are crucial contributions in ageing societies. The reason is that the human-robot communication can reduce the chances of the elderly having age-related diseases (e.g. dementia) [51, 56, 181] and improve their quality of life. Therefore, the robot partner needs to be imbued with biological competent cognitive intelligence to *guess* (refer to embodied cognitive intelligence definition of this thesis definition 1.6.7) the meaning and context of game interactions with the elderly. It is to increase forming a natural communication in the game interaction.

A novel biological stress-inspired model for the robot partner's embodied cognitive intelligence with dynamic optimisation on its working memory is proposed for the social support. The novel robot partner's cognitive framework is named *Advanced Intelligence Cognitive Optimisation (AICO)*. The AICO framework is a server-side framework for the high computational requirement for the robot partner's embodied cognitive intelligence processing. The AICO framework incorporates the optimisation operators discussed in Chapter 4 and apply them to the robot partner's working memory optimisation for embodied cognitive intelligence.

The physical robot partner that implements the AICO framework is the iPhone smartphone robot known as iPhonoid. Physical robot pilot test with the proposed iPhonoid AICO framework simulated in Rényi-Ulam guessing game are conducted with human test subjects in this chapter. The proposed AICO framework approach can successfully reduce the robot's guessing counts in the pilot test game interactions. Meanwhile, the robot partner's cognitive behaviour changes with respect to its different stress emotional conditions can make the gameplay more interesting.

5.2 Introduction

A cost-effective iPhone robot known as *iPhonoid* is utilised for the pilot testing of the AICO framework. As effective human-robot communications are important in a game's interactions, the robot partner needs to be biologically competent in its embodied cognitive intelligence to enhance the overall game experience with the elderly people. This chapter proposes a novel stress-based biological-inspired method to implement human *cognitive load* working memory processing [165] (subsubsection 2.4.7.2 for cognitive load's details) to optimise the robot partner's guessing of its human user intention. Cognitive load is also known as the proactive control in dual mechanisms of cognitive control [26] (definition 1.8.1).

A novel robot partner's embodied cognitive intelligence framework inspired from biological stress models for working memory dynamic optimisation is introduced. In Yerkes and Dodson's [186] stress curve explanation in subsection 2.4.3, the agent stress arousal level is comparable to a Gaussian-like relationship to the agent's cognitive performance. Lupien et al. [104] recently improved Yerkes and Dodson's early discovery by demonstrating the agent's stress arousal relation to its *working memory retrieval performance*. The *working memory retrieval performance* of an agent refers to the agent's potential to retrieve its past working memories. The term *working memory* has been defined in subsubsection 2.4.4. In general, a robot partner's working memory is its short-term memory that temporally stores memories in limited memory space; it is also a highly volatile memory.

According to Yerkes and Dodson's [186], initial stress pilot test on embodied cognitive intelligence, the agent's embodied cognitive intelligence will perform optimally only in *middle-stress arousal conditions*. Conversely, the embodied cognitive intelligence of the agent will be impaired in *low* and *high*-stress arousal conditions.

In short, the stress arousal level and working memory of an agent are highly related to an agent's cognitive performance. Therefore, a novel stress-inspired robot partner's embodied cognitive intelligence working memory optimisation framework is modelled with evolutionary computation (EC) dynamic optimisation algorithms [167, 168] in this chapter. The proposed model regulates the robot partner's stress arousal level and optimises its working memory in real-time.

In this pilot test's physical robot configuration, the proposed model dynamically optimises the robot partner's working memory to *derive or guess* the human-robot interactions output effectively. In other words, it is to implement the cognitive load's [165] working memory processing behaviours for the robot partner to guess the user's thinking process. The reason is that the human test subject may give additional environment context information to the robot partner in later game interactions.

A detailed and recent survey paper by Leite et al. [97] gave several reviews on human-robot long-term interactions in robot partner research. However, only one research study in Stubbs et al. [160] examined model capabilities from the cognitive intelligence point of view. Also, the fundamentals of cognitive intelligence science for robot partner and embodied cognitive intelligence were discussed by Pfeifer and Scheier [135].

Meanwhile, in current cognitive intelligence development for robot partners, Kubota [88] had proposed a cognitive intelligence with associative memory learning for human-robot communications. In Kubota's [88] work, the robot partner learns about the associations between perceived concepts with spiking neural network and evolutionally computation in spatial-temporal EC optimisation learning. Furthermore, Woo and Kubota [185] proposed a human-robot conversational system using a structured cognitive model; the system is integrated with a visual concept detection module with spiking neural network optimisation and evolutionary computation. However, in their proposed model [185] the maximum total detectable visual concepts count is limited, and the relationships between visual concepts and the words uttered may not have any semantic relationship at all.

Hence, these research gaps need to be addressed with the introduction of a model based on the robot partner's stress inspired embodied cognitive intelligence to have better human-robot interactions with the elderly people. Moreover, a novel model is needed to address the issue of hierarchical natural data representation of semantic concept relations. A module for large-scale and real-time visual image concepts detection is also necessary for natural human-robot interactions. Therefore, representations of human expert knowledge base [98] and hierarchical structured natural data of convolutional neural network [96] are integrated into the proposed model in this chapter.

5.3 Motivation for Pilot Test

In an ageing nation, the lack of communication stimulation for the elderly people in their lifestyle could increase their chances of getting different mental diseases such as dementia and Alzheimer's diseases [51, 56, 181] as mentioned in subsection 1.2.2. Furthermore, as these mental diseases may lead to many mental problems such as declines in attention, planning and memory ability, they face serious impacts on their lives such as accidents and health problems. Hence, the robot partner is designed to interact with these elderly people to reduce these mental diseases.

5.4 Objectives of Pilot Test

The main research objective of this chapter is to improve the elderly's interaction with a robot partner using the Rényi-Ulam guessing game. Furthermore, the robot partner's dynamic working memory optimisation methods are also tested for its optimisation efficiency in the Rényi-Ulam guessing game.

5.5 The Rényi-Ulam Guessing Game Problem

A mathematical game named the Rényi-Ulam guessing game [138, 177] is utilised in the pilot testing of the proposed model. A popular social game named *the 20 questions* is very similar to the Rényi-Ulam's guessing game.

In the Rényi-Ulam game, the primary player will try to guess an unknown object's concept with only 20 "Yes" or "No" responses from the quiz giving player. Then, it is assumed that the responded answers will not contain any false information or lies. If the number of questions is denoted by $q = 20$ for 20 questions to be asked of the primary player, every question and response can decrease half the object's concept guessing difficulty regarding the possibility. Hence for a Rényi-Ulam game with 20 questions, the primary player can differentiate $2^q = 2^{20} = 1,048,576$ concepts about the object.

In the pilot test physical setting for this chapter's research, an iPhonoid robot partner will act as the Rényi-Ulam primary player that will ask $q = 20$ questions to the human test subject who serves as the quiz giving player. As an example, the iPhonoid robot partner will ask the human test subject questions such as, "Is this a doll?" Subsequently, the human test subject will respond with "Yes" or "No" to the iPhonoid robot partner. Moreover, the iPhonoid robot partner will dynamically optimise its working memory to generate better-guessed questions to ask the human test subject with the help of clues from the human test subject.

The variance setting in this chapter when compared to the original Rényi-Ulam guessing game is that the robot partner is *can see* the guess object. Nevertheless, the robot partner's vision ability is bounded by only $1,000$ image concepts in its detection ability. Thus, the additional seeing ability of the robot partner in this chapter will not differ much from the original Rényi-Ulam guessing game. Additionally, in the proposed model, the *Overfeat* framework [147] can only detect $1,000$ image concepts in its framework. However, the Overfeat framework's limitation can be omitted with the *Open Cyc* inference system [98] with ($\geq 239,000$) concepts in its semantic concept inference ontology framework.

In this pilot test, the Open Cyc inference system represents the robot partner's *long-term semantic memory* as mentioned in subsubsection 2.4.5.2. In short, the proposed framework is not an object detection application but is the robot partner's guessing framework with the help of its limited image concept detection capability and extensive human general knowledge inference system. Thus, the proposed framework for the robot partner can enable it to derive a best-guessed answer with optimised working with support from vision and verbal clues from the human test subject.

5.6 Biological Stress-Inspired Embodied Cognitive Intelligence Model for Working Memory Dynamic Optimisation

It is known that an agent will react to an unknown situation from the environment with some stress hormones introduced into its hypothalamic-pituitary-adrenal (HPA) axis stress response system as discussed in subsection 2.3.1. This stress reaction phenomenon is also named *relative stress* [111] (as mentioned in Subsection 2.4.2) if an unknown concept or situation is given to an agent.

At low and high-stress arousal levels for the agent, the agent's embodied cognitive intelligent performance will be impaired, according to Yerkes and Dodson [186]. In contrast, when an agent is at the middle-stress arousal level, then the agent will exhibit optimum embodied cognitive intelligence performance to *derive a new intuition* as illustrated in Figure 5.1, depicting the different conditions that need different new intuition creation working memory scopes at various stress arousal levels.

Subsequently, when the agent faces an unknown problem, it is defined as the *non-stationary environment*. The agent has not anticipated the sudden event or change in the environment. As a result, to solve the non-stationary environment problem a process of constructing a new intuition is taken, named as the agent's *embodied cognitive intelligence*.

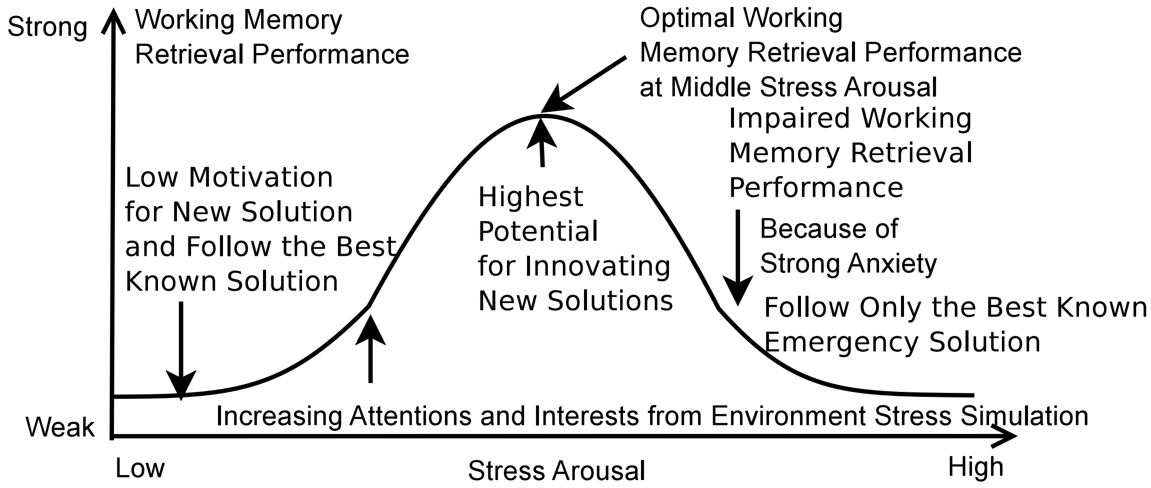


Figure 5.1: Improved Version of Yerkes and Dodson's Stress Curve [104, 186].

As mentioned earlier, Lupien at el. [104] showed that an agent's stress arousal and working memory retrieval performance are related. Interestingly, in a recent discovery on the evolutionary computation of dynamic optimisation problems [33], memory plays a significant role in solving the problems regarding performance gain. Hence, it is intuitive to apply dynamic optimisation to the model robot partner's working memory. Lupien et al.'s [104] inspire the proposed model in this chapter with their biological stress arousal Gaussian relationship with the robot partner's working memory retrieval performance as given in Equation 5.1.

Let the number of wrong answers answered by the human test subject be given by n_{wa}. In the low-stress arousal situation ($n_{wa} \approx 0$), in the simulation, the robot partner has confidence in the game with minimum optimisation of its working memory (less memory processing). In the middle-stress arousal situation ($n_{wa} \approx 10$), the robot partner is alert of the game's difficulties and starts to optimise its working memory holistically. Finally during a high-stress arousal condition, the robot partner loses the game when wrong answers are about to be given ($n_{wa} \approx 20$); this simulates the robot partner to show a lack of interest or frustration or reluctance to process its working memory into guessing a correct answer. The robot partner's emotional responses to the above three simulation scenarios give a realistic game interaction experience as if it is emotionally interacting with human a player.

In short, the robot partner's stress arousal level h_{gc} (glucocorticoid stress hormone) will be equal to $n_{wa}/20$, where $0 \leq n_{wa} \leq 20$, as computed from clues given by the human test subject. In Figure 5.1, h_{gc} is the horizontal axis. Then, c_{wm}, the stress-based coefficient for the working memory retrieval performance, is the vertical axis in the figure and is computed with the robot partner's stress arousal level h_{gc}:

$$c_{wm} = \exp\left(-\frac{(h_{gc} - \mu)^2}{2\sigma^2}\right), \tag{5.1}$$

where σ is the standard deviation and μ is the mean of the proposed robot partner's stress inspired model's configurations.

5.7 Dynamic Bacterial Memetic Algorithm

Furthermore, the proposed model is an extension of Botzheim et al.'s [21] stationary EC approach named the Bacterial Memetic Algorithm (BMA) that simulates the bacterial evolution process. As explained in Chapter 4, the original BMA improved its optimisation operators, which are bacterial mutation and gene transfer operators, with the proposed approaches of *Dynamic Programming Gene Transfer (DPGT)* [168] in section 4.7 and *Average Edit Distance Bacterial Mutation (AEDBM)* [167] in section 4.12.

Then a novel robot partner's working memory dynamic optimisation model is introduced, named the Dynamic Bacterial Memetic Algorithm (DBMA). This DBMA algorithm is proposed because of its good optimisation performance in discrete optimisation problem domain such as the robot partner's working memory. Since the robot partner's working memory or short-term memory is *acoustic processing based* [100], in this proposed approach a table of strings is used to represent the acoustic nature of the robot partner's working memory. The proposed DBMA optimisation approach can subsequently remove the irrelevant concepts in the robot partner's working memory corresponding to concept clues provided by the human test subject. In other words, the concept clues are given by the human test subject are the evaluation function criteria during the optimisation process. The clues are given by the human player in the Rényi-Ulam guessing game act as the *intention* for the robot partner to optimise its working memory towards the intention's goal.

The biological stress-inspired working memory optimisation model is then needed because it simulates the robot partner's guessing ability during different stress arousal situations. The robot partner's dynamic working memory optimisation problem is illustrated in Figure 5.2. Let X be defined as the total working memory space for

Algorithm 8 Dynamic Bacterial Memetic Algorithm

```
procedure DBMA
    Update Working Memory X as bacterial population
    generation ← 0
    while generation ≠ N_gen do
        for row = 1 ... rounded(N_bac · c_wm) do
            AEDBM(X_row)
        for row = 1 ... rounded(N_bac · c_wm) do
            LocalSearch(X_row)
        DPGT(X)
        generation ← generation + 1
```

the robot partner, then x as the subset of its working memory scope is only activated during a different stress arousal level h_{gc} (glucocorticoid stress arousal level).

Next, i is denoted as the total width of the robot partner's working memory space. The possible robot partner's working memory space limits are $i = 1, 2, \ldots, 7$ where i represents the width vector dimension. However, working memory space can have more than 7 stored concepts as mentioned by Cowan [38]. Furthermore, the robot partner's maximum concepts to be held at its working memory is set to be the same as the human's working memory capacity of seven concepts [121]. The plus and minus two concepts in Miller's work [121] are removed for model simplicity. However, Cowan [38] explained the human's working memory capacity can be higher than 7 ± 2 concepts. Therefore, the robot partner's working memory can be extended to 7×7 concepts in this research assumption.

Then, the dynamic glucocorticoid optimisation in this chapter is elaborated as Equation 5.2 where the cost function $f(x_t)$ at time t is not the same as $f(x_{t+1})$:

$$arg \min_{x_t} f(x_t) \neq arg \min_{x_{t+1}} f(x_{t+1}), \quad where\, x \subseteq X,\, \forall t \tag{5.2}$$

The proposed DBMA approach (Algorithm 8) is a stochastic optimisation method applied to a bacterial population (as represented as the robot partner's working memory). It combines local and global stochastic search operators to find a partial-optimal solution at given time t. Regarding stochastic global search, this DBMA approach integrates the AEDBM [167] operator with the DPGT [168] operator. Concerning stochastic local search, Open Cyc [98] human expert knowledge base is utilised to optimise the string concepts in the robot partner's working memory into a more precise string concept representation. For example, a "dog" concept becomes a more accurate concept such as "Siberian husky".

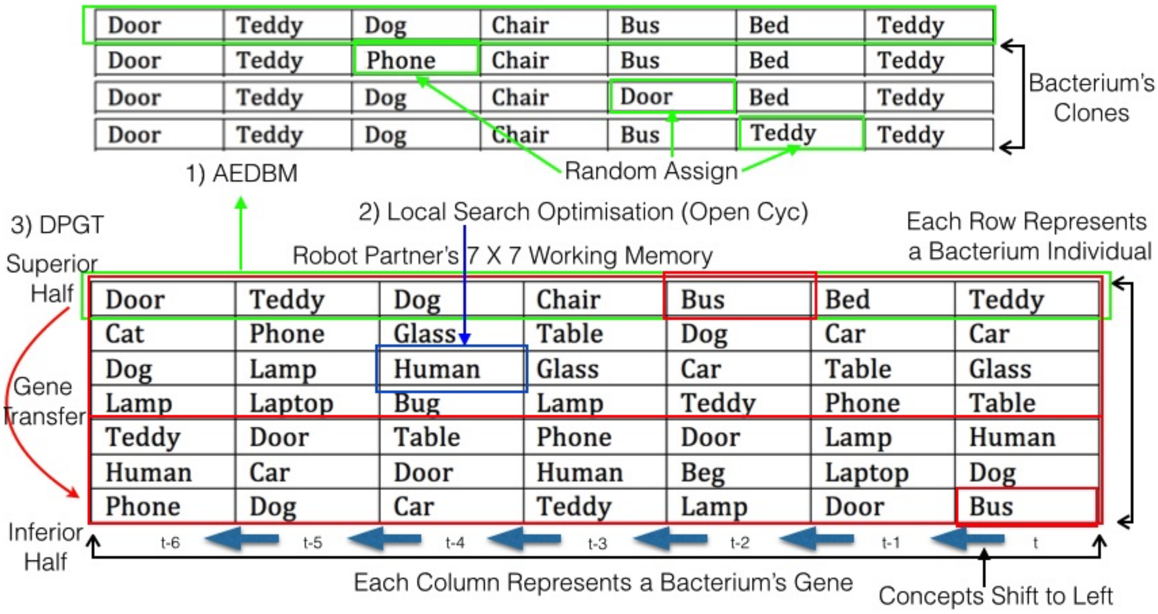


Figure 5.2: Robot Partner's Working Memory Encoding for DBMA Optimisation.

The proposed DBMA approach starts with the detection of new concepts from Overfeat's [147] visual image concept detection framework, then stores the newly detected concepts in the right-most working memory space table in Figure 5.2. Denoting N_{bac} as the number of bacterial individuals, the proposed DBMA approach iterates until the number of generations N_{gen} stopping criterion is met. Then, the DBMA begins with the AEDBM operator, followed by the local search and DPGT operators.

5.7.1 Encoding

In the proposed DBMA model in Figure 5.2, the robot partner's working memory is modelled as a bacterium population for optimisation. Also, the robot partner's working memory is represented as a 7×7 strings matrix table (bacterial population) as illustrated in Figure 5.2. The *row* in the strings matrix table is an individual bacterium's chromosome while the *column* in the row is the bacterium's gene information.

The new concepts detected from the Overfeat framework [147] is assigned to the time t column at the most right. Consequently, all the concepts in the robot partner's working memory are shifted to one column to the left. The left-most concepts (old concepts) in the working memory are overwritten completely. This shifting of working memory concepts simulates the behaviour of volatile memory in the agent's working memory.

5.7.2 Evaluation

As mentioned, the optimisation evaluation criteria are computed with clues given from the human test subject's answers in the Rényi-Ulam guessing game. If Z denotes the given wrong answer concepts of a vector of strings, where $1 \leq |Z| \leq 20$, n_{col} is denoted as the total width of the robot partner's working memory. Furthermore, a *row* is defined as the current bacterium ID that is chosen for evaluation where $1 \leq row \leq 7$.

Dynamic Rényi-Ulam optimisation of the robot partner's working memory as illustrated in Algorithm 8 step 2 where robot partner's working memory is updated, in this chapter context, means the optimisation is done on the population that is constantly updated. For example, the working memory stored concepts are always updated with new concepts detected from the environment:

$$\sum_{col=1}^{n_{col}} \sum_{v=1}^{n_{wa}} e \leftarrow e + EditDistance(X_{row,col}, Z_v) \tag{5.3}$$

$$eval = e/(n_{col} \cdot n_{wa}) \tag{5.4}$$

The accumulated error, denoted as e, is computed from the comparison between the human test subject's given clues on wrong answer concepts Z and individual clone's gene $X_{row,col}$. Furthermore, evaluation of the individual bacterium performance is denoted as *eval* with the Z total clues from the human test subject.

5.7.3 Edit Distance

The minimum edit distance between two concept strings, calculated based on dynamic programming, is explained in Chapter 4 by Algorithm 7 [99]. The edit distance calculation is for similarity comparison between the two string concepts.

5.7.4 Bacterial Mutation

The proposed DBMA performs the AEDBM [167] operator first in the DBMA algorithm and the AEDBM operator processes the bacterial mutation in the bacterial population as illustrated in Figure 5.2 label 1 green box at the top. The diagram also shows how the two global search operators and a local search operator perform their optimisation processes. It is a modified AEDBM version from that given in Section 4.12 of Chapter 4 for the robot partner's working memory optimisation.

Algorithm 9 Average Edit Distance Bacterial Mutation

procedure AEDBM
    $edCount \leftarrow 0$
    $edSum \leftarrow 0$
    Create clones
    Random mutation order
    for $m := 1, 2 \ldots 7$ **do**
        $assign \leftarrow False$
        $cnt_{srch} \leftarrow 0$
        while $Not\ assign\ And\ cnt_{srch} < max_{search}$ **do**
            Random select bacterium m-th gene as a
            $total_{ED} \leftarrow 0$
            for $n := 2, 3 \ldots N_{clones} + 1$ **do**
                Random select n-th clone's gene as b
                $total_{ED} \leftarrow total_{ED} + editDistance(a, b)$
            $average_{ED} \leftarrow total_{ED}/N_{clones}$
            $edCount \leftarrow edCount + 1$
            $edSum \leftarrow edSum + average_{ED}$
            $averageEDThreshold \leftarrow edSum/edCount$
            if $average_{ED} \geq averageEDThreshold$ **then**
                Assign selected bacterial gene elements
                $assign \leftarrow True$
            $cnt_{srch} \leftarrow cnt_{srch} + 1$
        for $k := 1, 2 \ldots N_{clones} + 1$ **do**
            Evaluate the k-th clone
        Selection of the best clone
        Best clone transfers the genes to other clones
    Use the best clone as new bacterium

The main objective of the AEDBM operator is to improve the bacterium's gene. Next, in Algorithm 9, the AEDBM operator replicates N_{clones} number of clones from a selected bacterium individual. Then, these duplicated clones are subjected to a random concept assignment of new gene information. However, random assignments of gene information or detected concepts are limited by the scope of the Overfeat [147] $1,000$ image concepts. Moreover, the AEDBM operator conducts a similarity checking of all the clones' genes with average edit distance calculations using Algorithm 7 before assigning the gene information to other clones.

5.7.5 Local Search

The local search in the proposed DBMA approach integrates Open CyC [98] general knowledge inference system to optimise specifically the bacterium's gene information that is shown on label 2 blue box in the middle of Figure 5.2. The inference system that loads related reference memory into the agent's working memory is emphasised in Baar's global workspace theory [5] (subsection 2.5.7).

In each step of the local search loop, Open Cyc [98] human expert knowledge base is utilised to optimise the robot partner's working memory's column (gene information) to a specific concept. For instance, when a "dog" concept is selected in the robot partner's working memory, the local search operator will randomly apply a subclass to the chosen concept with more precise dog concepts such as "shih tzu", "beagle" and "poodle". This assignment of specific concepts is randomly executed only if the generated random probability value is more than the threshold α. The threshold α is part of the proposed DBMA approach's configuration settings.

5.7.6 Gene Transfer

The final algorithm step in the proposed DBMA approach is the horizontal gene transfer operator known as the DPGT operator [168] (Algorithm 10). It is a modified DPGT operator version from Chapter 4 (section 4.7) for optimising the robot partner's working memory.

The term horizontal gene transfer is about the process of transferring the genes from a superior bacterial group to the inferior bacterial group, illustrated in the labelled 3 red boxes at the bottom of Figure 5.2. In short, the DPGT operator permits the gene's information to be transferred between the different bacterial individuals in a population as illustrated in Figure 5.2.

Thus, the bacterial population is categorised into two bacterial groups according to their sorted fitness values. However, the DPGT operator only optimises the whole bacterial population once, in contrast to the AEDBM operator and local search operator which optimise on each bacterium individual in the population. The DPGT operator compares the destination and source gene's elements string's similarity by edit distance calculation based on Algorithm 7 before conducting the gene transfer operation. The DPGT operator's infection frequency is set by the N_{inf} parameter, which is an pilot test configuration setting in the DBMA approach.

Algorithm 10 Dynamic Programming Gene Transfer

```
procedure DPGT
    edCount ← 0
    edSum ← 0
    for m := 1, 2 ... N_inf do
        Order Population into two halves
        Random Source Bacterium
        Random Destination Bacterium
        assign ← False
        cnt_srch ← 0
        while Not assign And cnt_srch < N_search do
            Select Source Bacterium's Gene as a
            Select Destination Bacterium's Gene as b
            d_{m,n} ← minEditDistanceCalc(a, b)
            edCount ← edCount + 1
            edSum ← edSum + d_{m,n}
            averageEDThreshold ← edSum/edCount
            if d_{i,j} ≥ averageEDThreshold then
                Assign Source to Destination Elements
                assign ← True
            cnt_srch ← cnt_srch + 1
```

5.8 Advanced Intelligence Cognitive Optimisation Framework

A novel robot partner framework, named Advanced Intelligence Cognitive Optimisation (AICO), is then introduced. Figure 5.3 explains the settings of the AICO framework. The proposed AICO framework is a server-based framework computational intensive cognitive processing of the Rényi-Ulam guessing game interactions. The image also states the communication flows of the AICO framework in the pilot test settings. For this chapter's pilot test setting, the iPhonoid robot partner is the thin client that only transfers images and verbal information to the AICO framework. The AICO framework is used to realise the Rényi-Ulam guessing game settings for the human test subject and the iPhonoid robot partner.

The AICO framework is a server side system consisting of four modules, i.e. that are *Open Cyc*, *Overfeat*, *MySQL* database and the *iPhonoid robot*. The *Open Cyc* inference system [98] is set as the iPhonoid robot's general knowledge base during the DBMA local optimisation as stated in subsection 5.7.5. The Open Cyc inference system [98] is to facilitate the iPhonoid robot partner to *guess* the meaning of the Rényi-Ulam guessing game context. In other words, it is to equip the iPhonoid robot

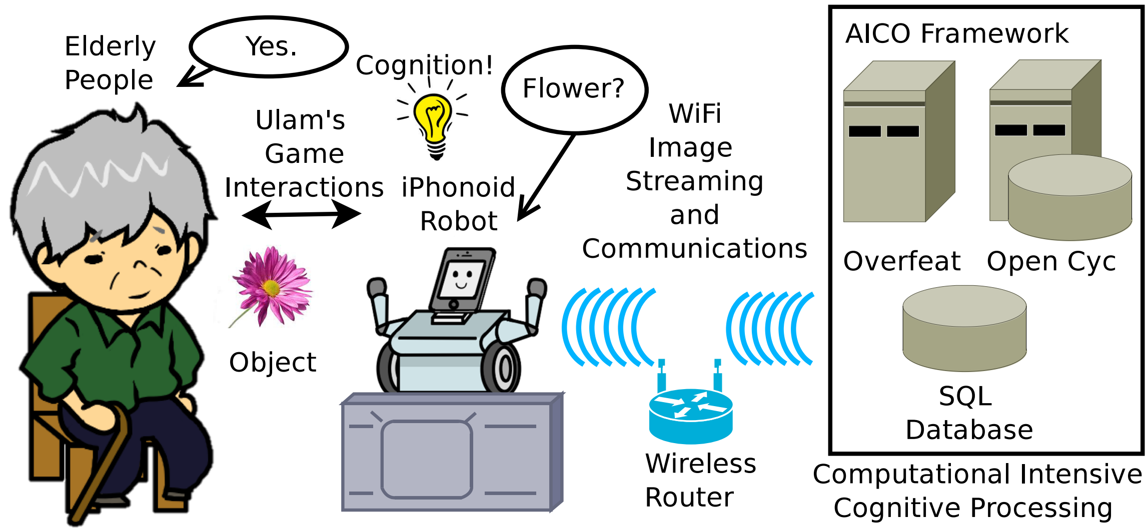


Figure 5.3: The Proposed AICO Framework.

partner's guessing ability with the general knowledge-based inference system that improves the overall human-robot game interactions.

Next, the *Overfeat* framework [147] is a convolutional neural network in a deep learning architecture that can detect $1,000$ image concepts. The Overfeat framework can compute its $1,000$ image concept detection in the AICO framework at 2 seconds per detection cycle. Finally, the iPhonoid robot partner is set as the thin client robot system for the physical Rényi-Ulam guessing game human-robot interaction with the elderly (Figure 5.4). The photo in Figure 5.4 is the physical iPhonoid robot partner prototype B. The iPhonoid robot partner is constructed with iPhonoid 4, A-12+ servos, Arduino controller and 3-D printable body [184].

5.9 Pilot Test Settings

The hardware settings are a MacBook Pro machine with 2.8 GHz Intel Core i7 processor and 16 GB 1600 MHz DDR3 RAM. The software settings are the operating systems Mac OS X 10.9.4. and the proposed DBMA approach is implemented in a C++ language application environment. Table 5.1 shows the proposed DBMA approach's optimisation parameter settings.

The Rényi-Ulam guessing game primary test objects are the teddy bear, laptop, bottle and clock concepts. Figure 5.5 is an example of the pilot test physical setting of the Rényi-Ulam guessing game with the teddy bear as a test object to be guessed in a human-robot game interaction. Since the Open Cyc inference system [98] needs

Table 5.1: The pilot test parameter settings for the proposed DBMA approach.

N_{gen}	N_{clones}	N_{inf}	α	N_{search}	μ	σ
10	3	3	0.7	5	0.5	4

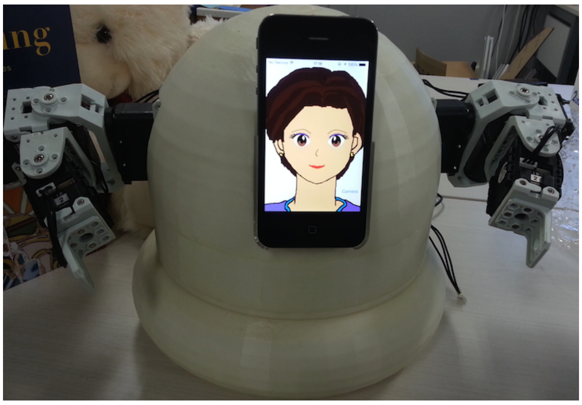


Figure 5.4: Robot Partner Image of the Physical iPhonoid [184].

2 seconds for each iteration cycle to process, the DBMA optimisation parameter settings in Table 5.1 are sensitive for the overall processing time needed per iteration cycle. Hence, correct tuning of the pilot test's parameter settings is needed for good real-time human-robot interaction. In the pilot test setting, adjusting the N_{gen} value parameter can control the needed computation time for the DBMA optimisation process. Furthermore by changing the N_{clones} parameter, the N_{inf} parameters will have fewer impacts on computation time. Lastly, changing the N_{search} pilot test parameter will have the lowest computation time effects.

In summary, the α is the main threshold percentage to control the local search process. If the generated random percentage value is bigger than α, then only the local search step is performed on the bacterium individual gene information. Furthermore, the parameter α is also set as the threshold percentage to choose the bacterium individual's gene information for local optimisation.

5.10 Pilot Test Results

The initial experimental results were conducted by me to pilot test the model. Chapter 7.11 is the wider study with (N=32) which concluded the effectiveness of the proposed model with a statistically significant study. I have updated the results to

Figure 5.5: Physical Rényi-Ulam Guessing Game Pilot Test.

show this through ANOVA and T-Test significance tests.

5.11 Chapter Summary

In the DBMA model, AEDBM [167] and DPGT [168] are combined to effectively tackle the optimization problems that require both exploratory and exploitation behaviour in the algorithms. This proved to be an effective way to balance between these two competing needs.

The study on the Rényi-Ulam game was a pilot test on the proposed model. I had chosen the Rényi-Ulam game because it had the elements of heuristic decision making, or guessing. After this pilot test I then moved onto verbal communication experiments and widened the study with a cross section of the university population (Chapter 7).

In this chapter, a novel Rényi-Ulam game is proposed as a pilot test in the AICO interaction embodied cognitive framework for the robot partner. The robot partner's working memory optimisation or *cognitive load* working memory processing can increase its guessing ability in the pilot test. The *cognitive load* was explained as a working memory processing phenomenon in subsubsection 2.4.7.2. The robot partner's working memory is fully optimised during its middle-stress arousal condition when it can achieve higher guessing performance.

5.12 Acknowledgment

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Chapter 6

Empirical Explanations for Proposed Spiking Reflective Processing Model

6.1 Overview

This chapter further investigates research question 2 (RQ2) of subsection 1.7.2, "Cognitive intelligence is said to be an important factor of human intelligence. What is it exactly? And what are the state-of-the-art cognitive models in current robot partner?". Specifically in this chapter, we will investigate the what is human's cognitive intelligence precisely. We assume the human's cognitive intelligence is the reflective processing model or System 2 in the perspective of the dual-processing cognitive process [55]. Initially, we will conduct a working memory experimental test on a human subject for reflective processing [151] with artificially induced stress with the *Life Experiences Survey* by Irwin G. Sarason et al. [144]. The robot partner spiking reflective processing model in the next chapter (Chapter 7) is created based on obtained working memory test result from the participants' behaviours in this chapter. The blurred displayed words ambiguity stimuli will trigger the human's reflective processing during the working memory test. We recorded the test subject's responses to survey forms and software inputs accordingly. Then, we conduct analysis on the experimental results to understand the human's reflective processing behaviours.

6.2 Introduction

There are two main subsections of introduction for this chapter; the first subsection is Stanovich [155] *dual-process theory* and the second subsection is Baddeley [9] multi-components working memory model:

6.2.1 Dual-process Theory

In this section, we focus on the discussion of the human's reflective processing behaviour during ambiguous situations. Many of the modern research literature discussions on reflective processing [151] are referring to the dual-process theory for a cognitive model. The dual-process theory was first coined by Stanovich [155]. The dual-process theory is the System 1 and System 2 processes for an agent's cognitive model. The dual-process theory is a well accepted reflective processing theory in psychology research community in recent time [2, 30, 47, 48, 55, 57, 76, 82, 151, 157, 172]. Evans [48] also provides better definitions for System 1 and System 2 process as below:

Definition 6.2.1. *System 1* is the decision-making process that is high capacity, fast, self-reliant of working memory and cognitive ability.

Definition 6.2.2. *System 2* is the decision-making process that is low capacity, slow, heavily dependent on working memory and related to individual different in cognitive ability.

Firstly, the System 1 in the dual-process theory cognitive model can be explained as agent's default heuristic system responses in a familiar environment and correct reactions to the environment is known. Secondly, System 2 is explained as reflective processing [151] or analytic system responses in an uncertain environment. System 2 it is unique to human only. For example, when a car driver is going to cross the traffic light if the traffic light system is normally functioning. Then, the person's default System 1 response is responsible for normal traffic light condition. In this normal traffic light condition, red light is to stop, and green light is to cross the road.

On the other hand, in an event of the traffic light system is faulty, the abnormal condition triggers the feeling of *ambiguity* or *disfluency* when the person realised the traffic light do not change its lights for some time. Then, the person's stress arousal level will build up to propel the body to react and mitigate the situation, and then the person System 2 response is activated by observing the environment context information ((*reflective*) of the traffic for other vehicle and cross the road accordingly. In short, the dual-process theory [48] explains the System 1 transition to System 2 during an event of ambiguity or disfluency conditions from the environment.

In this research, we agreed on the *default-interventionist* perspective on dual-process theory. In other words, the System 1 processes are operational by default upon for agent's action selection and decision making until otherwise interrupted by System 2 processes and working memory [47]. Alter et al. [2] investigated the feeling of *stress* or *disfluency* as a metacognitive cue to triggers System 2 activation, hence transition out of the default System 1 automatic processes. In another point of view, Thompson [172] had discussed the *feeling of rightness* that represents in this metacognitive capacity of monitoring behaviour. Besides, Inbar et al. [76] had studied the task characteristics of a metacognitive clue is a type of processing to trigger System 2 activation. For example, an experiment test to think quickly with *gut* feelings or by listing of reasons. Furthermore, Cacioppo and Petty [30] studied the individual differences approach for investigating the thinking dispositions such as a need for cognition. Also, researcher such as Betsch [19] studied the preference for deliberation and intuition that make System 2 activated more easily. Furthermore, De Neys and Glumicic [128] hypothesise there is a constant shallow analytic monitoring process conducted by System 2. In summary, default-interventionist perspective is a well-accepted explanation on dual-process theory in this research community.

Why we need the reflective processing model [151] for an artificially intelligent agent such as robot partner? The dynamic changes from the robot partner's environment may create an enormous impact on to the agent survival according to its ability to response to the unknown environment conditions as discussed in section 2.3. The robot partner timely action selection behaviour to react to the changing environment is crucial for its survival by adaptation. Hence, the robot partner should equip with reflective processing similar to human to response during any ambiguous situations where the solution is unknown. For example, during an emergency situation where the exit instruction displayed words are partly unreadable by the robot partner. The robot partner needs to be able to *guess* the unreadable words with given clues from the environment context information. Such guessing behaviour should be similar to human to maximise its survival with human-like response to the unknown environment. Therefore in this chapter, we investigate the human's reflective processing model on how human *guess* blurred texts that represent the ambiguous environment context information. Then, in Chapter 7 we apply the obtained reflective processing model (the human's guessing behaviours) in this chapter and apply it to the robot partner's guessing behaviours in human-robot communication application. In other words, the robot partner has to create new intuition to mitigate the ambiguous environment challenges that may require its quick response that similar to human.

In order construct an accurate model of the human reflective processing model, we need to model the human's reflective processing [55, 57, 151] behaviours with psychology working memory test experiments. The psychology test experiment will empirically capture the human's reflective processing or System 2 processing behaviours [55, 57, 151]. The obtained human reflective processing model in this chapter will be the main model for human-robot communication application for its responses during an ambiguous situation in the next chapter (Chapter 7).

6.2.2 Multi-Components Working Memory Model

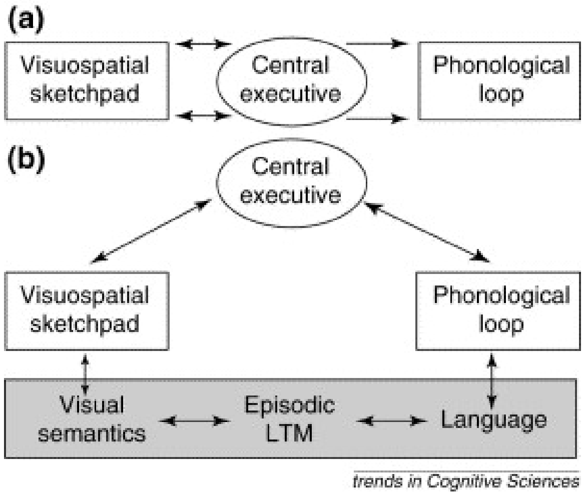

Figure 6.1: Multi-component working memory model [9]. *We obtained the permission to reuse the copyrighted diagram from Elsevier. ©Elsevier.*

Alan Baddeley [8] initially proposed multi-components working memory model that only consist of three components that are *central executive control*, *visuospatial sketchpad* and *phonological loop* (Figure 6.1a). Then, Baddeley published his latest multi-components working memory model that included an additional component called *episodic buffer* (Figure 6.1b) [9]. Phonological loop is part of agent's working memory component for storing speech-based information, for an example digits in the digit span test. On the other hand, the visuospatial sketchpad is part of agent's working memory component to setting up and processing visuospatial imagery. Next, central executive control is the agent's working memory component that performs switch attention, focus attention, divide attention and link to long-term memory. It is a purely attentions control system for the agent.

The episodic buffer [9] component is believed to be able of storing information into the working memory in the form of multi-dimensional code. The episodic buffer also provides a short-term interface between the slave systems of working memory system that are the phonological loop, visuospatial sketchpad and the long-term memory. The central executive control component controlled the episodic buffer component, which the central executive control component is responsible for binding information from many different sources into coherent episodes and stored in the episodic buffer. Furthermore, these created episodes in the episodic buffer are believed to be retrievable consciously by the agent. The binding information behaviour in episodic buffer component is an important concept for our proposed reflective processing model in subsection 6.3. The information binding phenomena in episodic buffer component is assumed to produce the agent's new idea during ambiguous condition reflective processing in our model.

In Figure 6.1 [9], the shaded areas in the diagram illustrate *crystallised* cognitive systems that responsible for forming long-term memory. On the other hand, the unshaded areas in Figure 6.1 describe the *fluid* capacities (e.g. temporary storage and attention). The episodic buffer serves as a modelling memory space that is distinct from long-term memory. However, it is a crucial stage for long-term episodic learning for the agent. Therefore, the agent's new intuition via reflective processing will be able to be stored in the form of crystallised long-term memory from episodic buffer [9] temporary storage form.

6.3 Proposed Spiking Reflective Processing Model

In Chapter 2, we select the synthetic modelling [135] research methodology (definition 2.1.1) for our model design consideration, we emphasise the different point of views from biological, psychological, philosophical and computational literature for incorporate them into our model design (Figure 6.2).

In biology literature point of view (section 2.3), we focus on agent's stress response system and working memory retrieval performance and its relationship with stress level [104]. In our assumption, the agent's stress response system is the trigger mechanism for System 1 to System 2 transition. The agent's ambiguity or disfluency resulted from the environment will act as the stimuli to trigger stress response system to release stress hormone into the agent's body. The System 2 is highly dependent on agent's working memory [48] on reflective processing (definition 6.2.2). Hence, we choose stress response system as the focus on biological literature point of view for our model design consideration in our proposed spiking reflective processing model (Figure 6.2).

Next, the psychology literature point of view (section 2.4), we focus on Baddeley's multi-component working memory model [9] (subsection 6.2.2). The reason is his multi-component working memory model has the episodic buffer component that

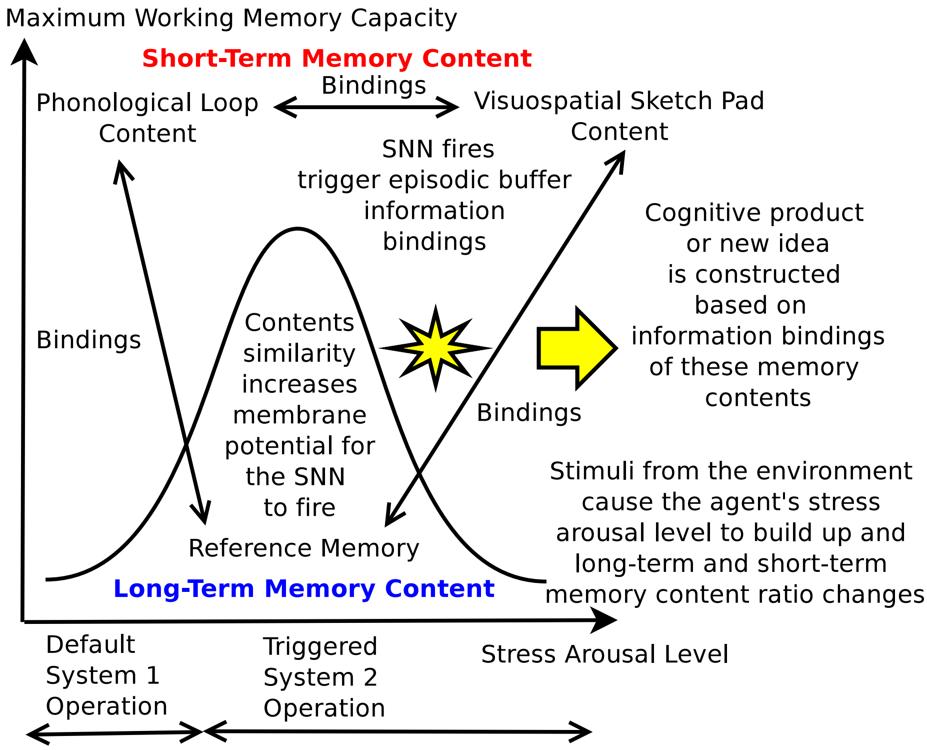

Figure 6.2: Spiking Reflective Processing Model.

binds different code of information contents (long-term memory content and short-term memory content) in the working memory and forms a new cognitive product or new intuition. Furthermore, it also supports our argument on our spiking reflective processing model (Figure 6.2) that indicates the cognitive product or new intuition is created after the Spiking Neural Network (SNN) [61] fires when SNN exceeded its membrane potential threshold. We also argue that similarity between long-term memory content and short-term memory content will increase the membrane potential threshold in SNN. Furthermore, we also consider the findings of short-term memory content impairment in the working memory with stress stimuli that was initially investigated by Klein and Boals [85]. Therefore, we choose Baddeley's multi-component working memory model [9] as our focus in psychological literature point of view for our model design consideration.

In philosophy literature point of view (section 2.5), we selected dual-process theory [156] for our model design consideration. The reason is dual-process theory highlighted the importance of working memory and stress arousal level for reflective processing concerning to agent's response in an uncertain environment. In bottom area of our model (Figure 6.2) illustrated that System 1 is the default agent response until the agent's stress arousal level reached a middle level that will trigger the activation of

System 2. The dual-process theory captured the agent's ambiguity or disfluency that causes System 1 to System 2 transition. Therefore, we choose dual-process theory for our model design consideration.

In computing literature point of view (section 2.6), we select Spiking Neural Network (SNN) model [61] for our model design consideration. We argued that the similarity between long-term memory content and short-term memory content in working memory will increase the SNN's membrane potential so that it will lead to SNN fire (spike). Then SNN fire event will trigger the episodic buffer information binding [9] of long-term memory content and short-term memory content. The yellow coloured star shape in our spiking reflective processing model (Figure 6.2) illustrate the newly created SNN spike event. Furthermore, in the point of view of computing literature, the similarity of agent's long-term memory content and short-term memory content in working memory can be measured with edit distance with dynamic programming algorithm [17] as discussed in Chapter 4. Hence, we focus on SNN model for our model design consideration.

Furthermore, the agent's long-term memory content and short-term memory content ratio in working memory are subject to change according to different stress arousal level [104] illustrated in the inverted-U shape in our model (Figure 6.2). The short-term memory content is the information stored in working memory that received from the environment context information. On the other hand, long-term memory content is the declarative memory (definition 2.4.3) that loaded into the working memory [85]. In general, during low and high-stress level conditions the short-term memory content in the working memory will have high memory retrieval performance because of low long-term memory content in agent's limited working memory capacity. In contrast, during middle-stress arousal condition, the long-term memory content in the working memory will occupy most of the agent's limited working memory capacity. Therefore short-term memory content in the working memory will have low memory retrieval performance. Hence, an inverted-U shape graph is visible on long-term memory content or declarative memory performance plotted against stress level [104].

In this chapter, the main different between reflective processing and our spiking reflective processing model is that we emphasise the importance of agent's stress arousal level, Spiking Neural Network (SNN) model [61] and episodic buffer information binding [9] for agent's new intuition creation behaviour. In following sections, we investigate our human participant's response with blurred text questionnaire test to validate our spiking reflective processing model. The human test subject long-term memory content and short-term memory content will be the primed for the test as controlled variables.

6.4 Motivation for Experiment

In the perspective to incorporate our proposed spiking reflective processing model (section 6.3) into the robot partner's embodied cognitive intelligence, we need to validate our proposed model with human participation experiments with established working memory and stress evaluation test.

6.5 Objective of Experiment

The objective of this chapter is to validate our proposed spiking reflective processing model with established working memory and stress evaluation test.

6.6 Hypothesis

The items below are null hypothesis for the experiment in this chapter:

- H_0: There is no significant difference among different long-term memory test trials in term of the long-term memory test score.
- H_1: There is no significant difference among different long-term memory test trials in term of the time taken in seconds for long-term memory test.
- H_2: There is no significant difference among different short-term memory test trials in term of the score for short-term memory test.
- H_3: There is no significant difference among different short-term memory test trials in term of the time taken for short-term memory test.
- H_4: There is no significant difference among different STAI test trial in term of the score.

6.7 Experimental Settings

We had randomly selected the total of thirty-two test subjects ($n = 32$) from Monash University Malaysia campus area by the personal approach to the test subjects. Then, we provide *explanatory statement form and consent* form (Appendix A.1) to the test subject. Next, we introduce our experiment aims and research descriptions to the selected test subject. If the test subject agreed to participate in our experiment, then he or she will need to sign the consent form to begin the experiment process.

After the test subject signed the consent form, he or she begins the experiment by filling in the *Perceived Stress Scale (PSS)* form [35] (Appendix A.2). The perceived stress scale form is to evaluate the test subject's feelings and thoughts about their events that happened one month before engaging in this experiment. The reason is to measure the factors that could influence the test subject's emotion and feeling in this experiment. Next, the test subject required to complete the *State-Trait Anxiety Inventory (STAI)* form [153] (appendix A.3) to measure his or her current emotion state before the experiment starts.

Subsequently, the test subject had filled in all the forms. Then, he or she will be proceeded to operate a Mac laptop with Python language GUI application programme for the experiment. Then, the participant will start fill-in the *life experiences survey* questions in the programme [144] (Appendix A.4). The reason for the life experiences survey is needed to stimulate the test subject to trigger the relative stress (subsection 2.4.2) by recalling the life events that he or she had experienced within a year before this experiment [144]. The life experiences survey also captures how much that the particular life event that had affected the test subject emotionally. Hence, these survey questions will be the stress arousal stimuli for the test subject. Two sets of life experiences survey questions are available such as adult and student life experience questions, different sets of survey questions will be given to the test subject according to their age group.

After the Python GUI application programme stimulated the test subject's stress arousal level, next the Python programme will start long-term memory content priming on the test subject's reference memory to memorise 12 words as described in Lupien et al. [106] work. The 12 words will be displayed to test subject as text on the monitor screen and the application will also read-out-loud with the text-to-speech feature (appendix A.5). For each time, the test subject needs to recall the 12 words can type into the form given in Python language GUI application programme. The whole process will repeat for four times. Then for the fourth time before the test subject key-in the answers, the test subject will be tested in his or her short-term memory content test (appendix A.6).

The establish psychology test methodologies from Sternberg's test [159] and Frederick's Cognitive Reflection Test (CRT) [57] inspired our experiment design. The test subject will be flashed with six words before he or she guesses the two words that are 50 percent blurred text. Then, the participant will be asked to fill in the remaining fourth trial of the long-term memory content test after short-term memory content test. Finally, the test subject needs to complete the *State-Trait Anxiety Inventory (STAI)* form [153] (appendix A.3) to measure his or her emotion state after the experiment ends.

6.8 Experimental Results

We had successfully gathered the experimental result data and included them in the appendix section of this thesis. Below is the list of data captured from the experiment:

1. Intuitive response questionnaire result (Appendix A.7).
2. The long-term memory content Python programme test result (Appendix A.8).
3. The short-term memory content Python programme test result (Appendix A.12).

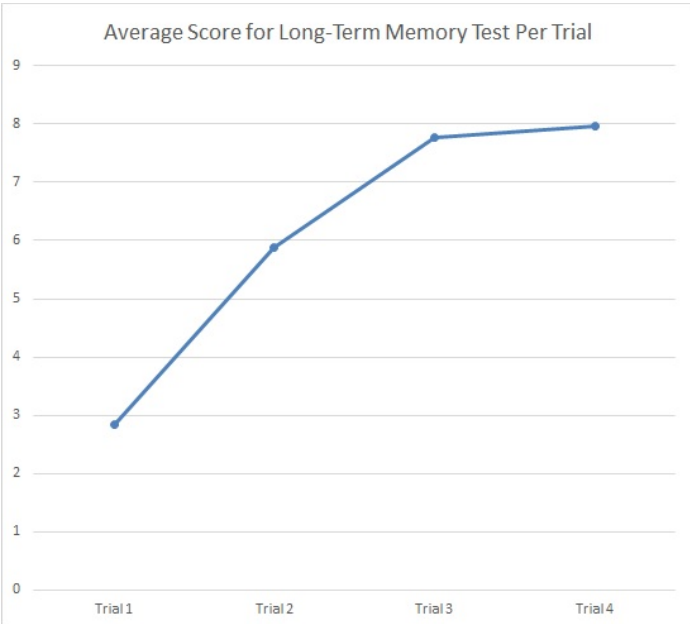

Figure 6.3: Average Score for Long-term Memory Test per Trial.

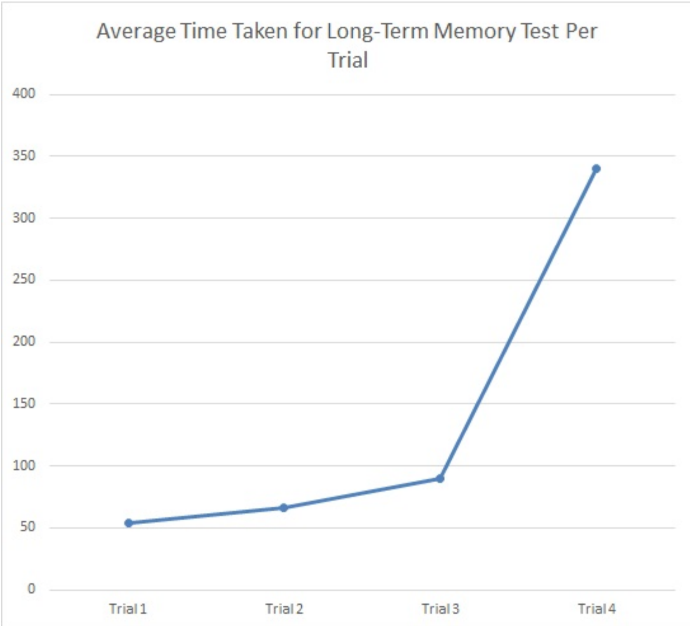

Figure 6.4: Average Time Taken for Long-term Memory Test per Trial.

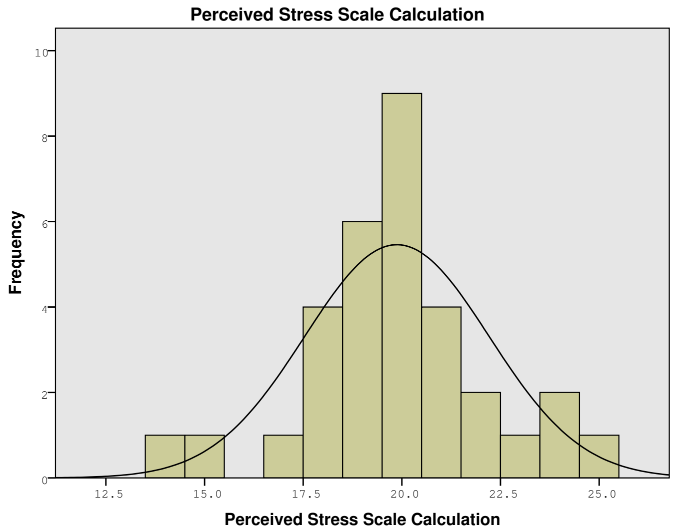

Figure 6.5: Perceived Stress Scale (PSS) total points bar chart.

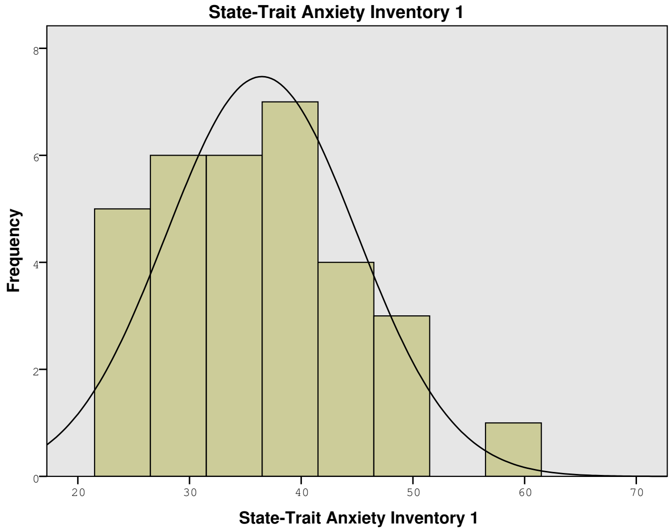

Figure 6.6: State-Trait Anxiety Inventory (STAI) test 1 total points bar chart.

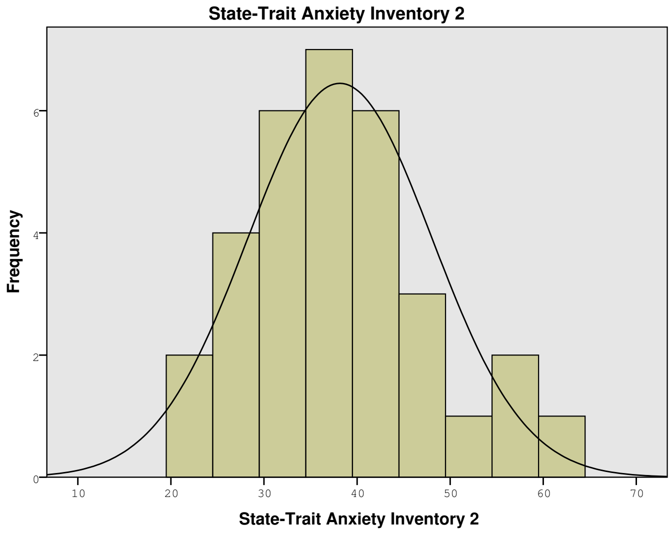

Figure 6.7: State-Trait Anxiety Inventory (STAI) test 2 total points bar chart.

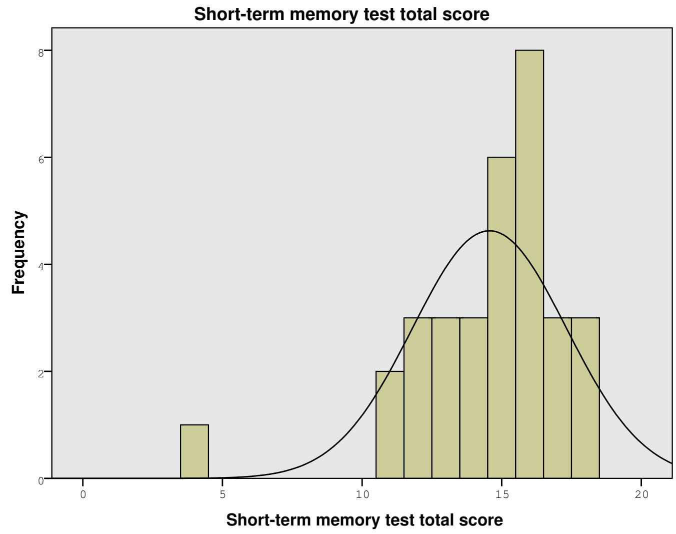

Figure 6.8: Short-term memory total score bar chart.

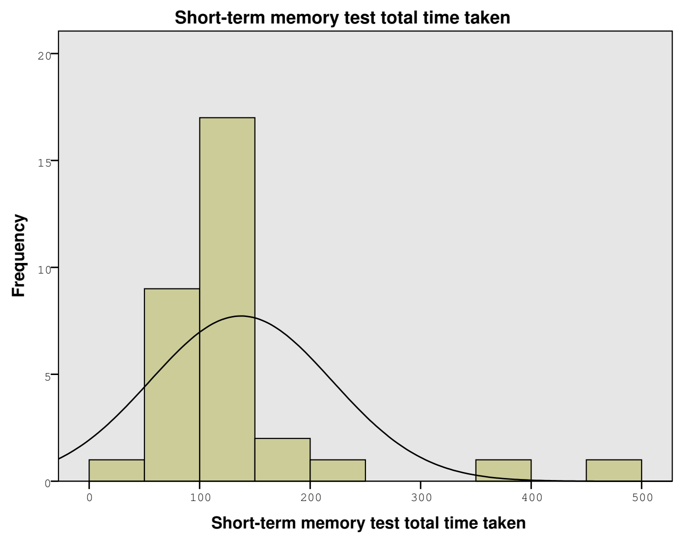

Figure 6.9: Short-term memory total time taken bar chart.

6.9 Analysis of Results

6.9.1 Normal Distribution Analysis

The graph (Figure 6.3) is the average score for the long-term memory test total score per trial. It revealed the participants long-term memory recall average score (average on all participants) are performing better from one trial to the next trial in the test. Bear in mind that the fourth trial long-term memory recall is after the short-term memory test is completed (that is after five to ten minutes later). Interestingly the fourth trial average recall score is slightly performing better than the third trial. It leads to our assumption that the similarity words in short-term memory test are enhancing the long-term memory average recall score overall performance. Although the short-term memory and long-term memory test words that are different but they are partially similar, please refer to the long-term memory test (Appendix A.5) and short-term memory test (Appendix A.6) for the partially similar test words. For example, the words *attack* and *attacking* are different but they are partially similar. Furthermore, the bar chart (Figure 6.4) on the average time taken for the long-term memory test enforces our claim that the long-term memory test fourth trial is taking longer time than usual as defined in System 2 definition 6.2.2. The System 2 processing is slow and highly dependent on working memory. Therefore, in our assumption during the long-term memory test fourth trial, the System 2 is activated. Hence, these empirically evidences supported our proposed spiking reflective processing model (hypothesis 1 and 2 in section 6.6) that similarity between short-term memory content and long-term memory content will increase the Spiking Neural Network (SNN) membrane potential. After SNN membrane potential exceeded its threshold and then the SNN will fire and initiates the System 2 response. The short-term memory content and long-term memory content in the working memory constructed the System 2 response content. The short-term memory test result (Appendix A.12) revealed the participant reply is a mix of short-term memory content and long-term memory content.

Statistics

		Perceived Stress Scale Calculation	State-Trait Anxiety Inventory 1	State-Trait Anxiety Inventory 2
N	Valid	32	32	32
	Missing	0	0	0
Mean		19.88	36.47	38.16
Median		20.00	36.00	39.00
Mode		20	26	39[a]
Std. Deviation		2.338	8.542	9.900
Skewness		-.114	.557	.589
Std. Error of Skewness		.414	.414	.414

a. Multiple modes exist. The smallest value is shown

Figure 6.10: State-Trait Anxiety Inventory (STAI) test 1, State-Trait Anxiety Inventory (STAI) test 2 and Perceived Stress Scale (PSS) statistic analysis table.

Statistics

		Short-term memory test total score	Short-term memory test total time taken
N	Valid	32	32
	Missing	0	0
Mean		14.56	137.50
Median		15.00	124.10
Mode		16	47[a]
Std. Deviation		2.758	82.596
Skewness		-1.872	2.903
Std. Error of Skewness		.414	.414

a. Multiple modes exist. The smallest value is shown

Figure 6.11: Short-term memory test scores and participant's time is taken to answer statistic analysis table.

Correlations

			Total score for short-term memory test	Total time taken for short-term memory test
Kendall's tau_b	Total score for short-term memory test	Correlation Coefficient	1.000	**-.449****
		Sig. (2-tailed)	.	**.001**
		N	32	32
	Total time taken for short-term memory test	Correlation Coefficient	**-.449****	1.000
		Sig. (2-tailed)	**.001**	.
		N	32	32
Spearman's rho	Total score for short-term memory test	Correlation Coefficient	1.000	**-.581****
		Sig. (2-tailed)	.	**.000**
		N	32	32
	Total time taken for short-term memory test	Correlation Coefficient	**-.581****	1.000
		Sig. (2-tailed)	**.000**	.
		N	32	32

**. Correlation is significant at the 0.01 level (2-tailed).

Figure 6.12: Kendall's tau b and Spearman's rho correlation coefficient analysis between total score and time taken in the short-term memory test.

The short-term test average recall score, long-term memory test average recall score, Perceived Stress Scale (PSS) survey result [35] and State-Trait Anxiety Inventory (STAI) survey result [153] revealed the Yerkes and Dodson's [186] inverted-U shape relationship attribute. The bar chart (Figure 6.5) is the PSS survey result scores. The PSS survey result scores distribution poised similarity to a normal distribution with a mean of 19.88 and with a minor negative skewness of -0.114 (Figure 6.10). Next, the bar chart (Figure 6.6) and (Figure 6.7) are the STAI survey results for the before and after the Python programme test. The STAI survey result scores distribution before the Python programme test indicates a normal distribution with a mean of 36.47 and with a moderate positive skewness of 0.557 (Figure 6.10). Then, the STAI survey result scores distribution after the Python programme test indicates a normal distribution with a mean of 38.16 and with a moderate positive skewness of 0.589 (Figure 6.10). Next, the bar chart (Figure 6.8) is the short-term memory test average result scores for correct guesses of blurred words. The short-term memory average result score distribution also indicated similarity to a normal distribution with a mean of 14.56 and with a negative skewness of -1.872 (Figure 6.8). Furthermore, the bar chart (Figure 6.9) is the short-term memory test average time taken guesses of the blurred words. The short-term memory test average time result's distribution also illustrated similarity to a normal distribution with a mean of 137.5 and with a positive skewness of 2.903 (Figure 6.11). These bar charts exhibited the inverted-U shape (normal) relationship that is similar to Yerkes and Dodson's [186] stress model (Chapter 2 subsection 2.4.3). Then, these bar charts also supported our proposed *spiking reflective processing* stress model (Section 6.3). They indicated the inverted-U shape structure relationship between the short-term memory content and long-term memory content in the working memory. The strong positive Kendall's tau b and Spearman's rho correlation coefficient statistical analysis (Figure 6.12) enforces our argument. These correlation coefficients statistical analysis indicated that the participants activated their System 2 to archive better accuracy for answering the correct result with slower reply speed (longer time taken) as stated in System 2 definition 6.2.2.

6.9.2 One-Way ANOVA Analysis: Long-term Memory Test Trial and Score

In Figure 6.13, the descriptive statistics show that variations exist across the different long-term memory test trial in users' score in these tests. Trial 4 group obtained the highest mean long-term memory test score (Mean = 7.97; S.D. = 2.609) while trial 1 group obtained the lowest (Mean = 2.84; S.D. = 1.609). In Figure 6.14, Levene's test (.071) shows that the groups are homogenous in their variances (p (Sig.) > 0.05). This means that the standard deviations do not deviate greatly among the groups. Similarly, in Figure 6.17, the Homogeneous Subsets of both Tukey HSD test and Scheffe test show no significant differences among the different trials in the long-term memory tests, as all $p > 0.05$.

Long-Term Memory Test Score

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
Trial 1	32	2.84	1.609	.284	2.26	3.42	0	6
Trial 2	32	5.88	2.091	.370	5.12	6.63	1	10
Trial 3	32	7.78	2.612	.462	6.84	8.72	0	12
Trial 4	32	7.97	2.609	.461	7.03	8.91	1	12
Total	128	6.12	3.050	.270	5.58	6.65	0	12

Figure 6.13: Descriptives

Long-Term Memory Test Score

Levene Statistic	df1	df2	Sig.
2.396	3	124	.071

Figure 6.14: Test of Homogeneity of Variances

Long-Term Memory Test Score

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	543.086	3	181.029	35.176	.000
Within Groups	638.156	124	5.146		
Total	1181.242	127			

Figure 6.15: ANOVA

Dependent Variable: Long-Term Memory Test Score

	(I) Trial	(J) Trial	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Tukey HSD	Trial 1	Trial 2	-3.031*	.567	.000	-4.51	-1.55
		Trial 3	-4.938*	.567	.000	-6.41	-3.46
		Trial 4	-5.125*	.567	.000	-6.60	-3.65
	Trial 2	Trial 1	3.031*	.567	.000	1.55	4.51
		Trial 3	-1.906*	.567	.006	-3.38	-.43
		Trial 4	-2.094*	.567	.002	-3.57	-.62
	Trial 3	Trial 1	4.938*	.567	.000	3.46	6.41
		Trial 2	1.906*	.567	.006	.43	3.38
		Trial 4	-.188	.567	.987	-1.66	1.29
	Trial 4	Trial 1	5.125*	.567	.000	3.65	6.60
		Trial 2	2.094*	.567	.002	.62	3.57
		Trial 3	.188	.567	.987	-1.29	1.66
Scheffe	Trial 1	Trial 2	-3.031*	.567	.000	-4.64	-1.42
		Trial 3	-4.938*	.567	.000	-6.54	-3.33
		Trial 4	-5.125*	.567	.000	-6.73	-3.52
	Trial 2	Trial 1	3.031*	.567	.000	1.42	4.64
		Trial 3	-1.906*	.567	.013	-3.51	-.30
		Trial 4	-2.094*	.567	.005	-3.70	-.49
	Trial 3	Trial 1	4.938*	.567	.000	3.33	6.54
		Trial 2	1.906*	.567	.013	.30	3.51
		Trial 4	-.188	.567	.991	-1.79	1.42
	Trial 4	Trial 1	5.125*	.567	.000	3.52	6.73
		Trial 2	2.094*	.567	.005	.49	3.70
		Trial 3	.188	.567	.991	-1.42	1.79

*. The mean difference is significant at the 0.05 level.

Figure 6.16: Multiple Comparisons

Long-Term Memory Test Score

	Trial	N	Subset for alpha = 0.05 1	2	3
Tukey HSD[a]	Trial 1	32	2.84		
	Trial 2	32		5.88	
	Trial 3	32			7.78
	Trial 4	32			7.97
	Sig.		1.000	1.000	.987
Scheffe[a]	Trial 1	32	2.84		
	Trial 2	32		5.88	
	Trial 3	32			7.78
	Trial 4	32			7.97
	Sig.		1.000	1.000	.991

Means for groups in homogeneous subsets are displayed.
a. Uses Harmonic Mean Sample Size = 32.000.

Figure 6.17: Homogeneous Subsets

Figure 6.15 shows the ANOVA output. Looking at the output, we can say that there are significant differences among the different long-term memory test trial in terms of user's test score (F = 35.176; df = 3; $p < 0.05$). From Figure 6.16, based on the Tukey HSD test and Scheffe test, there is a significant difference between the long-term memory test user's score of trial 1 and trial 2. Similarly, there is a significant difference between trial 2 and trial 3, and also trial 1 and trial 3, as $p < 0.05$. However, only trial 3 and 4 have no significant difference as $p > 0.05$. The reason is the trial 3 and 4 have no significant difference because the participant can adapt to the long-term memory test in the later trial 3 and 4.

Based on Figure 6.15 and Figure 6.16, we should conclude that *the null hypothesis h_0 is rejected*, and hence the long-term memory test trial differ significantly in their user's score of the long-term memory test. In other words, the participants can memorise long-term memory better with more long-term memory test trials.

6.9.3 Welch and Brown-Forsythe Analysis: Long-term Memory Test Trial and Time Taken

In Figure 6.18, the descriptive statistics show that variations exist across the different long-term memory test trial in users' time taken in these tests. Trial 4 group obtained the highest mean long-term memory test score (Mean = 339.79; S.D. = 101.830) while trial 1 group obtained the lowest (Mean = 54.33; S.D. = 29.468). In Figure 6.19, Levene's test (.000) shows that the groups are not homogenous in their variances (p (Sig.) < 0.05). This means that the standard deviations deviate greatly among the groups. However, in Figure 6.21, the Homogeneous Subsets of both Tukey HSD test and Scheffe test show no significant differences among the different trials in the long-term memory tests, as all $p > 0.05$.

Long-Term Memory Test Time Taken In Seconds

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
Trial 1	32	54.33	29.468	5.209	43.70	64.95	7	125
Trial 2	32	66.28	28.851	5.100	55.88	76.69	18	144
Trial 3	32	89.43	35.434	6.264	76.65	102.20	26	186
Trial 4	32	339.79	101.830	18.001	303.07	376.50	211	718
Total	128	137.46	131.021	11.581	114.54	160.37	7	718

Figure 6.18: Descriptives

Long-Term Memory Test Time Taken In Seconds

Levene Statistic	df1	df2	Sig.
7.373	3	124	.000

Figure 6.19: Test of Homogeneity of Variances

Long-Term Memory Test Time Taken In Seconds

	Statistic[a]	df1	df2	Sig.
Welch	78.519	3	66.697	.000
Brown-Forsythe	176.805	3	49.796	.000

a. Asymptotically F distributed.

Figure 6.20: Robust Tests of Equality of Means

Long-Term Memory Test Time Taken In Seconds

	Trial	N	Subset for alpha = 0.05	
			1	2
Tukey HSD[a]	Trial 1	32	54.33	
	Trial 2	32	66.28	
	Trial 3	32	89.43	
	Trial 4	32		339.79
	Sig.		.076	1.000
Scheffe[a]	Trial 1	32	54.33	
	Trial 2	32	66.28	
	Trial 3	32	89.43	
	Trial 4	32		339.79
	Sig.		.122	1.000

Means for groups in homogeneous subsets are displayed.
a. Uses Harmonic Mean Sample Size = 32.000.

Figure 6.21: Homogeneous Subsets

Figure 6.20 shows the Welch and Brown-Forsythe analysis output. Looking at the output, we can say that there are significant differences among the different long-term memory test trial in terms of user's time taken in seconds in the Welch test (F = 78.519; df1 = 3; df2 = 66.697; $p < 0.05$) and Brown-Forsythe analysis output (F = 176.805; df1 = 3; df2 = 49.796; $p < 0.05$).

Based on Figure 6.20, we should conclude that *the null hypothesis h_1 is rejected*, and hence the long-term memory test trial differ significantly in their user's score of the long-term memory test trial. We conclude that is the participant's long-term memory is being supported by the short-term memory test trial. Therefore, the participant long-term memory retrieval will be getting better in the later long-term memory test trials. Hence, it requires the user to have more time to derive the answers by exhaustive search of his or her memory.

6.9.4 Welch and Brown-Forsythe Analysis: Short-term Memory Test Trial and Score

In Figure 6.22, the descriptive statistics show that variations exist across the different short-term memory test trial in users' score in these tests. Trial 5 and 7 groups obtained the highest mean short-term memory test score (Mean = 1.72; S.D. = 0.523) while trial 1 group obtained the lowest (Mean = 1.31; S.D. = 0.738). In Figure 6.23, Levene's test (.035) shows that the groups are not homogenous in their variances (p (Sig.) < 0.05). This means that the standard deviations deviate greatly among the groups. However, in Figure 6.25, the Homogeneous Subsets of both Tukey HSD test and Scheffe test show no significant differences among the different trials in the short-term memory tests, as all $p > 0.05$.

Short-Term Memory Test Score

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
Trial 1	32	1.31	.738	.130	1.05	1.58	0	2
Trial 2	32	1.56	.716	.127	1.30	1.82	0	2
Trial 3	32	1.66	.602	.106	1.44	1.87	0	2
Trial 4	32	1.56	.619	.109	1.34	1.79	0	2
Trial 5	32	1.72	.523	.092	1.53	1.91	0	2
Trial 6	32	1.66	.545	.096	1.46	1.85	0	2
Trial 7	32	1.72	.523	.092	1.53	1.91	0	2
Trial 8	32	1.69	.471	.083	1.52	1.86	1	2
Trial 9	32	1.66	.602	.106	1.44	1.87	0	2
Trial 10	32	1.59	.665	.118	1.35	1.83	0	2
Total	320	1.61	.608	.034	1.55	1.68	0	2

Figure 6.22: Descriptives

Short-Term Memory Test Score

Levene Statistic	df1	df2	Sig.
2.033	9	310	.035

Figure 6.23: Test of Homogeneity of Variances

Short-Term Memory Test Score

	Statistic[a]	df1	df2	Sig.
Welch	.978	9	126.179	.462
Brown-Forsythe	1.252	9	288.179	.263

a. Asymptotically F distributed.

Figure 6.24: Robust Tests of Equality of Means

Short-Term Memory Test Score

	Trial	N	Subset for alpha = 0.05 1
Tukey HSD[a]	Trial 1	32	1.31
	Trial 2	32	1.56
	Trial 4	32	1.56
	Trial 10	32	1.59
	Trial 3	32	1.66
	Trial 6	32	1.66
	Trial 9	32	1.66
	Trial 8	32	1.69
	Trial 5	32	1.72
	Trial 7	32	1.72
	Sig.		.186
Scheffe[a]	Trial 1	32	1.31
	Trial 2	32	1.56
	Trial 4	32	1.56
	Trial 10	32	1.59
	Trial 3	32	1.66
	Trial 6	32	1.66
	Trial 9	32	1.66
	Trial 8	32	1.69
	Trial 5	32	1.72
	Trial 7	32	1.72
	Sig.		.617

Means for groups in homogeneous subsets are displayed.

a. Uses Harmonic Mean Sample Size = 32.000.

Figure 6.25: Homogeneous Subsets

Figure 6.24 shows the Welch and Brown-Forsythe analysis output. Looking at the output, we can say that there are no significant differences among the different short-term memory test trial in terms of user's score in the Welch test ($F = 0.978$; $df1 = 9$; $df2 = 126.179$; $p > 0.05$) and Brown-Forsythe analysis output ($F = 1.252$; $df1 = 9$; $df2 = 288.179$; $p > 0.05$).

Based on Figure 6.24, we should conclude that *the null hypothesis h_2 is accepted*, and hence the short-term memory test trials do not differ significantly in their user's score of the short-term memory test. The reason is each trial in the short-term memory test is having different randomly selected questions and its score are not depending the accumulation of previous trial memory.

6.9.5 Welch Analysis: Short-term Memory Test Trial and Time Taken

In Figure 6.26, the descriptive statistics show that variations exist across the different short-term memory test trial in users' time taken in these tests. Trial 1 group obtained the highest mean for short-term memory test time taken in seconds (Mean = 28.21; S.D. = 33.864) while trial 10 group obtained the lowest (Mean = 10.47; S.D. = 5.033). In Figure 6.27, Levene's test (.000) shows that the groups are not homogenous in their variances (p (Sig.) < 0.05). This means that the standard deviations deviate greatly among the groups. However, in Figure 6.29, the Homogeneous Subsets of both Tukey HSD test and Scheffe test show no significant differences among the different trials in the short-term memory tests, as all p > 0.05.

Short-Term Memory Test Time Taken in Seconds

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean: Lower Bound	95% Confidence Interval for Mean: Upper Bound	Minimum	Maximum
Trial 1	32	28.21	33.864	5.986	16.00	40.41	7	182
Trial 2	32	13.94	10.991	1.943	9.97	17.90	2	48
Trial 3	32	12.51	8.665	1.532	9.39	15.63	4	50
Trial 4	32	13.28	10.349	1.829	9.55	17.02	3	56
Trial 5	32	12.21	10.610	1.876	8.39	16.04	5	61
Trial 6	32	11.86	7.612	1.346	9.11	14.60	4	40
Trial 7	32	11.34	8.778	1.552	8.17	14.50	4	43
Trial 8	32	10.88	7.801	1.379	8.07	13.69	3	42
Trial 9	32	12.81	12.046	2.129	8.46	17.15	3	69
Trial 10	32	10.47	5.033	.890	8.65	12.28	3	24
Total	320	13.75	14.551	.813	12.15	15.35	2	182

Figure 6.26: Descriptives

Short-Term Memory Test Time Taken in Seconds

Levene Statistic	df1	df2	Sig.
3.667	9	310	.000

Figure 6.27: Test of Homogeneity of Variances

Long-Term Memory Test Time Taken In Seconds

	Statistic[a]	df1	df2	Sig.
Welch	78.519	3	66.697	.000

a. Asymptotically F distributed.

Figure 6.28: Robust Tests of Equality of Means

Short-Term Memory Test Time Taken in Seconds

	Trial	N	Subset for alpha = 0.05 1	2
Tukey HSD[a]	Trial 10	32	10.47	
	Trial 8	32	10.88	
	Trial 7	32	11.34	
	Trial 6	32	11.86	
	Trial 5	32	12.21	
	Trial 3	32	12.51	
	Trial 9	32	12.81	
	Trial 4	32	13.28	
	Trial 2	32	13.94	
	Trial 1	32		28.21
	Sig.		.992	1.000
Scheffe[a]	Trial 10	32	10.47	
	Trial 8	32	10.88	
	Trial 7	32	11.34	
	Trial 6	32	11.86	
	Trial 5	32	12.21	
	Trial 3	32	12.51	
	Trial 9	32	12.81	
	Trial 4	32	13.28	
	Trial 2	32	13.94	13.94
	Trial 1	32		28.21
	Sig.		.999	.055

Means for groups in homogeneous subsets are displayed.
a. Uses Harmonic Mean Sample Size = 32.000.

Figure 6.29: Homogeneous Subsets

Figure 6.28 shows the Welch analysis output. Looking at the output, we can say that there are significant differences among the different short-term memory test trial in terms of user's time taken in the Welch test (F = 78.519; df1 = 3; df2 = 66.697; p < 0.05).

Based on Figure 6.28, we should conclude that *the null hypothesis h_3 is rejected*, and hence the short-term memory test trials differ significantly in their user's time taken for the short-term memory test. The reason is all short-term memory test questions are randomly selected, hence different trials require different time duration to answer the question.

6.9.6 T-Test Analysis: Form Sessions and STAI score

In Figure 6.30, the descriptive statistics show that variations exist across the different STAI test in users' score in these tests. Trial 2 group obtained the highest mean STAI score (Mean = 38.16; S.D. = 9.9) while trial 1 group obtained the lowest (Mean =

36.47; S.D. = 8.542). In Figure 6.27, Levene's test (.648) shows that the groups are homogenous in their variances (p (Sig.) > 0.05). This means that the standard deviations do not deviate greatly among the groups.

	Form Session	N	Mean	Std. Deviation	Std. Error Mean
State Trait Anxiety Inventory (STAI)	Trial 1	32	36.47	8.542	1.510
	Trial 2	32	38.16	9.900	1.750

Figure 6.30: Group Statistics

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
State Trait Anxiety Inventory (STAI)	Equal variances assumed	.211	.648	-.730	62	.468	-1.688	2.311	-6.308	2.933
	Equal variances not assumed			-.730	60.698	.468	-1.688	2.311	-6.310	2.935

Figure 6.31: Independent Sample Test

Figure 6.31 shows the T-Test analysis output. Looking at the output, we can say that there are significant differences among the different short-term memory test trial in terms of user's time taken in the T-test (F = 0.211; df = 62; p > 0.05).

Based on Figure 6.31, we should conclude that *the null hypothesis h_4 is accepted*, and hence the form sessions do not differ significantly in their STAI test. Therefore, the participants are not extremely stressed by the STAI test but middle-stress stimuli introduction is assumed for the form sessions. The reason is the overall STAI test score had been increased.

6.10 Contributions

The three items are the main contributions of this chapter:

1. We discovered that the similarity between short-term and long-term memory contents in the working memory increased the short-term and long-term memory test average scores but with slower response speed. We argued this slower response speed be due to the participants' System 2 activation. The experimental results supported our proposed spiking reflective processing model hypothesis 1 (Section 6.6).

2. We discovered that the participants' System 2 short-term test replied answers are the combinations of short-term and long-term memory contents in the working memory. The experimental results enforced our proposed spiking reflective processing model hypothesis 2 (Section 6.6).

3. These experimental results from the previous two items supported our proposed spiking reflective processing model (Section 6.6). We conducted our experiment with the established working memory evaluation methodology in psychology research field. Our experimental design also utilised the widely used Perceived Stress Scale (PSS) and State-Trait Anxiety Inventory (STAI) participant's state evaluation survey approaches.

6.11 Chapter Summary

In the first introduction of this chapter, we discussed the importance of dual-process theory for our model design considerations. The dual-process theory is a well-establish theory in the field of psychology research on cognition. We argued that the System 2 be the key system that enables the reflective processing that leads to any response in the ambiguous situation.

In the second introduction of this chapter, we emphasised the importance of Alan Baddeley's [9] multi-components working memory model in our model design considerations. Particularly, we focus on episodic buffer component of the working memory system because of the information binding attribute that it exhibits. We argued the episodic buffer component be the key part of agent's new intuition creation behaviour that binds long-term and short-term memory contents together.

We proposed our spiking reflective processing model with synthetic modelling [135] methodology (definition 2.1.1) consideration. In the synthetic modelling point of view, we considered the biological, psychological, philosophical and computational literature point of view before proposing our model. Furthermore, our proposed model hypothesis 1 and hypothesis 2 are supported by the empirical evidence from participants in a university population. In the next chapter, we will implement our proposed spiking reflective processing model into a robot partner embodied cognitive intelligence for human-robot communication application to support the users socially.

Chapter 7

Spiking Reflective Processing Model for Human-Robot Communication Application

7.1 Overview

This chapter is to implement the human's spiking reflective processing (Chapter 6 section 6.3) model into human-robot communication application. We want to investigate how to address better the human-robot communication problem with the focus on Smerek's reflective processing model [151] in the perspectives of working memory, Spiking Neural Network (SNN) and stress response system (subsection 2.3.1). The reflective processing model is the System 2 in dual-process theory [155] that is low capacity, slow, highly correlated with working memory in cognitive ability. The dual-process approach theory was first coined by Stanovich [155].

Reflective processing is a System 2 processing behaviour in dual-process approach where the response produced is highly dependent on agent's working memory during an ambiguous situation. For an example, in a faulty traffic light condition (ambiguity), the car driver has to be vigilant to the surrounding traffic conditions (high working memory usage for storing surrounding information) and to determine the right time to cross the road (guessing). Hence, reflective processing or System 2 processing is also the system that processes the robot partner response during ambiguous interaction conditions during human-robot communication scenarios. In this research, we hypothesise the robot partner reflective processing can increase the human-robot communication engagement.

Next, this chapter also addresses the research question 3 (RQ3) in subsection 1.7.3 "Can we improve the state of the art cognitive intelligence for robot partners by applying biological principles?". We proposed spiking reflective processing model (section 6.3) to enhance the human-robot communication experience in a daily conversations application. Investigating the robot partner solution in socially improving the elderly's living environment is a priority research area for developed nations as discussed in Section 1.2 of Chapter 1; it may be a key to improving their quality of life. However, the greatest challenge for this research area is developing a technology that can be comfortable with elderly people. In this chapter hypothesis, the robot partner's spiking reflective processing model (section 6.3) will improve the human-robot communication and thus improve the user acceptance of robot partner.

Furthermore, our proposed spiking reflective processing model (section 6.3) in previous Chapter 6 can be implemented for human-robot communication, we apply our model to different age groups of users other than elderly people. The human-robot communication should not be limited to elderly only because elderly may be living with the different age group of users, for example, relatives, health care workers, welfare workers and children. It is important that the robot partner can communicate with all different age group of users that living with elderly people for real-world practical application of this technology.

Towards this end, a novel human-robot cognitive interaction framework is developed to enable the robot partner to support the elderly people and other age groups of users socially. The proposed framework build an idea that term as "spiking reflective processing" that is the robot partner's *new intuition creation* or *new intention construction.* The new intuition creation behaviour occurs during reactive control mode in dual mechanisms of cognitive control [26] (definition 1.8.1) of agent's embodied cognitive intelligence. The model in this chapter extends the Chapter 5 agent's working memory optimisation model. Thus, the proposed model in this chapter exhibits the agent's new intuition creation or heuristic [149] behaviour with the range of possible environment context information in its working memory.

7.2 Introduction

In an ageing nation, the number of elderly people in the society constitutes a high percentage of the population. With the increasing population of the elderly, those not able to take care of themselves have also increased. Most of these elderly have mobility issues or chronic mental health disease. As such, they do not have much opportunity to socialise with other people. In the long term, this social isolation will cause cognitive decline in mental diseases (e.g. dementia or Alzheimer's disease) to these elderly.

Besides, the elderly's cognitive decline of memory, planning and attention may have a catastrophic impact on them (e.g. accident). Hence, the robot partner solution makes a significant contribution to socially supporting the elderly. At the same time, the robot partner needs to operate with a different age group of users that support the ageing society as discussed before. Leite et al. [97] who surveyed many different robot partner solutions to long-term human-robot communication showed the importance of robot partner approach. Nevertheless, these robot partner solutions [97] are not human's behaviours inspired models and may not operate optimally in a human living environment. Hence, we need to integrate the human's spiking reflective processing model (Chapter 6 section 6.3) into robot partner; it is because for robot partner to operate in an ambiguous and challenging conditions in a real-world environment for better user acceptance of this technology.

7.3 Motivation for Experiment

Essentially I need a model that works in real-time and is able to adaptively learn causal relationships between previously unknown concepts. The combination of GA with SNN fulfilled both of these criteria.

Bayesian networks [58] are one of the primary methods for making, and evaluating decisions. Traditional methods generally represent causal relationships between concepts given within a fixed structure and make decisions through learnt conditional probabilities. Adaptive Bayesian networks [31] can adapt their structures towards new input data. However, these adaptations require substantial time to reach convergence and where deemed as not suitable for my purposes.

Spiking Neural Network (SNN) [61] offered a good model for my work, they are fully connected structures and serve the purpose to discover patterns or features in the data stream in real-time.

Figure 7.1 illustrates the impact of different machine learning scenarios. Part (a) in Figure 7.1 shows a conventional machine learning and decision-making test without our proposed SNN model. Here, a standard converged Artificial Neural Network (ANN) machine learning approach is used for decision-making. The figure shows that the robot is behaving sub-optimally, incurring significant damage because of non-real-time nature of the machine-learning algorithm used and the delayed decision-making, damage to the robot in part (a) is maximum (the method is unable to adapt itself to the situation in real-time). On the other hand, part (b) uses my Spiking Reflective Processing model (Figure 6.2) and as illustrated it minimizes the damage to the robot (maximizing performance) by performing early decision-making with a sub-optimal learned model after the SNN spiked. It is important to have fast adaptive learning in real world robot applications to maintain the robot's self-preservation (survival) [161] as mentioned in Chapter 1 and 2.

Deep learning [96] does outperform many other pattern recognition learning algorithms, especially over large training datasets [141]. The deep learning model is inspired from convolutional neural networks [95] and comprise of many layers of connected neurons. Deep learning neural network models are commonly viewed as a "black box" learning models. It is very difficult, if feasible at all, to extract an understanding of why the model is performing the way it is, and why it is making the decisions it is. However, SNNs can be readily interpreted and understood, as illustrated by diagram Figure 7.3, each neuron represents memory object in my model. I require this "inspection" property to allow the GA in interpret, adapt and optimize the working the of SNN, and so optimize the working and operation of the memory model, as illustrated by Figure 5.2.

These are the main reasons that I have selected GA and SNN models because of their model's structural properties as mentioned as above.

Although the SNN exhibits many similarities to the continuous neural network [94] approach such as a large number of hidden units. However, the continuous neural net does not include the spike behaviour that is crucial for decision-making behaviour in our proposed model that based on similarity comparison in working memory contents.

7.3.1 An Application to Care Robot System

Constant interactions between the robot partner and the elderly person can reduce the latter's cognitive decline by stimulating his or her brain through human-robot communications. Thus, it is important that the robot partner can response or *guess* the environment context information to have better engaging daily conversations with the elderly and other age groups of users. This guessing ability is the *trial-and-error* behaviour to gain awareness of the environment information and react accordingly from the environment context information. In Regan and Kevin work [132], a *sensorimotor approach* for an agent is defined as the solution to the hard problem of feel or phenomenal consciousness from the agent's environment. Furthermore, the *heuristic technique* in subsection 2.4.7 described the robot partner can consciously generate new ideas efficiently to resolve the dynamic challenges posed by the environment context information. For example, the robot partner should not pause too long to reply

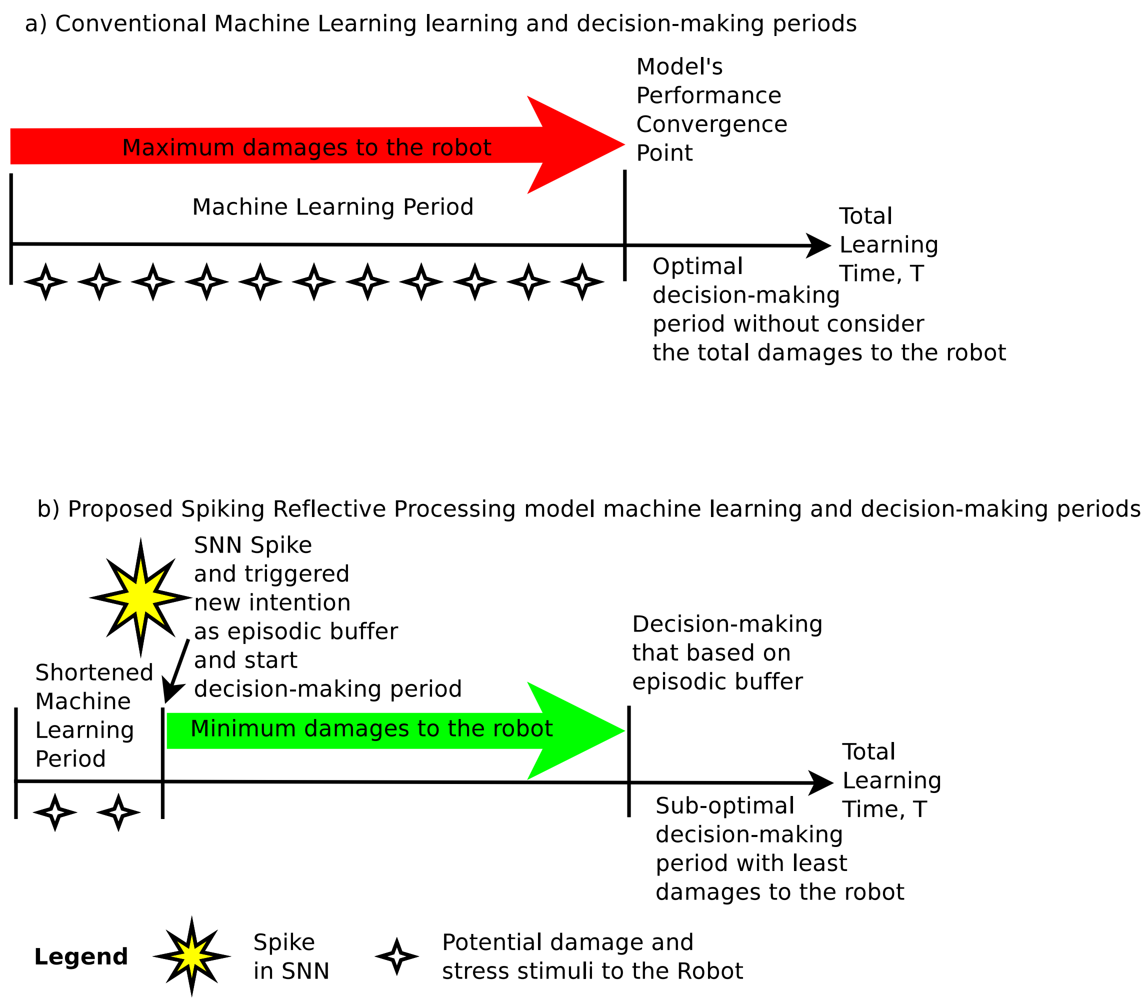

Figure 7.1: Conventional versus Spiking Reflective Processing model machine learning and decision-making Periods.

during a human-robot conversation. The heuristic technique [134, 149, 176] should be used to generate the communication dialogue efficiently.

In this chapter, a heuristic technique [134, 149, 176] behaviour is assumed to occur during the reactive control in dual mechanisms of cognitive control [26] (definition 1.8.1). The heuristic technique for this chapter is used interchangeably as System 2 or reflective processing in dual-process theory as discussed in Chapter 6. For instance, when the robot partner is spiking reflective processing (section 6.3) its new intuition that based on its working memory content. Information that is temporarily withholding in the working memory consists of the short-term memory content of environment context information and long-term memory content referenced into working memory. Therefore, the newly generated intention should be constructed with both short-term memory content and long-term memory content in the working memory.

In other words, it is crucial for the robot partner to have spiking reflective processing (section 6.3) cognitive intelligence or heuristic technique to understand the environment context information and efficiently generate conversational dialogues with its user. The robot partner needs to apply its heuristic technique to conduct context-aware communication through its spiking reflective processing (section 6.3) and its intuition creation response. For example, the robot may start a new dialogue about the weather after noticing an umbrella in its environment. The dialogue replied is not a previously stored dialogue but is dynamically generated with the help of the surroundings information and with the robot partner's heuristic mechanism. In summary, the robot partner novel response should be relevant and triggered from the environment context information as discussed in Chapter 6.

7.4 Objective of Experiment

The objective is to investigate the possibility of utilising our discovered spiking reflective processing model (section 6.3) cognitive intelligence for robot partner to improve the overall quality of life for the elderly and other age groups of users through human-robot interaction with emphasis on uncertain environment context information.

7.5 Hypothesis

The items below are null hypothesis for the experiment in this chapter:

- H_0: There is no significant difference between before and after negative attitude toward situations of interaction with robots.
- H_1: There is no significant difference between before and after negative attitude toward social influence of robots.
- H_2: There is no significant difference between before and after negative attitude toward emotions in interaction with robots.

7.6 Human-Robot Application with Spiking Reflective Processing Model

Many different perspectives of cognitive science and embodied cognitive science for artificial life have been revealed by Pfeifer and Scheier [135]. The terms *cognitive intelligence* and *embodied cognitive intelligence* have been discussed in Chapter 1 in definition 1.6.6 and definition 1.6.7. We use these terms embodied cognitive intelligence and spiking reflective processing interchangeably in this thesis because both terms are related to the perspectives of stress arousal level, working memory and response behaviour during ambiguous situations.

Embodied cognitive intelligence is a concept that extends the brain's functionality with the person's homeostatic mechanism that maintains the balance of the individual's body system functionality as well as his or her cognitive intelligence performance. In contrast, the initial cognitive science's perspective only considers the brain's cognitive capabilities without recognising the importance of a person's body homeostatic mechanism that could influence the cognitive processing. However, the human's stress response system as discussed in Chapter 2 subsection 2.3.1 is a set of organs that works almost independently from the brain. In addition to that stress hormone have many influences in working memory retrieval performance and cognitive intelligence as discussed by Lupien et al. [106] and Klein and Boals [85]. In this thesis, we argue that robot partner should have similar embodied cognitive intelligence model for Smerek's reflective processing [151] for it to react in any given ambiguous situations to enhance human-robot interaction engagement.

As mentioned in Chapter 2 in subsection 2.4.3, Yerkes and Dodson [186] first discovered the inverted-U shape relationship between cognitive intelligence and stress arousal level (Figure 7.2). Figure 7.2 also shows the robot partner's intuition creation needs in different stress arousal levels. Next, the occupation ratio window for

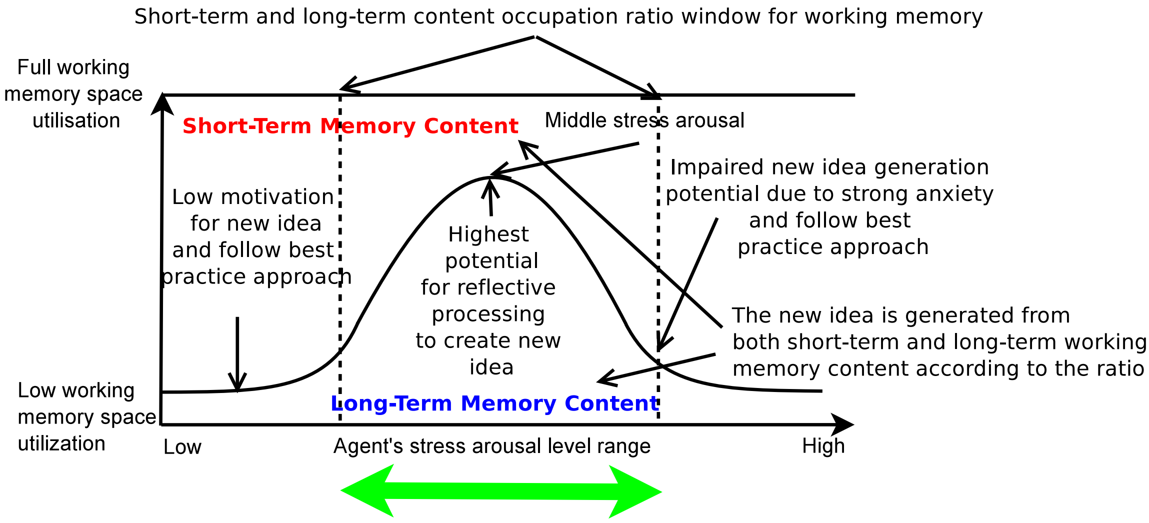

Figure 7.2: Improved Yerkes and Dodson Stress Diagram [186] with spiking reflective processing model and new intuition creation explanation.

short-term memory content and long-term memory content is also illustrated in Figure 7.2. This window frame (denoted as dotted lines) stretches for a range of agent's current stress arousal level. The upper area (red) of the graph is the short-term memory content from the environment. For example, short-term memory content is the context information from the environment such as audio input, visual input and tactile inputs that stored in working memory temporarily. The lower area (blue) of the graph is the long-term memory content is the reference memory triggered and loaded into the working memory. For example, a visual input of umbrella may trigger reference memory of rain loads into the working memory that based on a semantic relationship of the concepts. The ratio relationship between the long-term memory content and short-term memory content in working memory is similar to the Yerkes and Dodson [186] discovery of inverted-U shape phenomena.

Initially, Klein and Boals [85] investigated the impairment of short-term memory content in working memory with stress stimuli. In Chapter 6, we further develop the Klein and Boals [85] model into the model as illustrated in Figure 7.2 of the working memory impairment behaviours by life event stress stimuli. The window frame can slide to the right if stress stimuli from the environment increases or vice-versa. The window frame illustrates the ratio of short-term memory content and long-term memory content changes as the window frame sliding to the left and the right. Then, as mentioned in Chapter 2 in subsection 2.4.6, Lupien et al. [104] further described the discovery of Yerkes and Dodson [186] with the human's working memory retrieval performance that has the normal (inverted-U shape) relationship with human stress arousal. The human biological stress hormone creation and suppression homeostatic mechanisms are managed by the hypothalamic-pituitary-adrenal (HPA) axis system as mentioned in Chapter 2. The HPA stress response system in human communicates to other parts of the human body with stress hormones such as epinephrine and glucocorticoid.

As discussed in Chapter 2, in subsection 2.4.2, in an event when a new environment is given to stimulate the person, a mild stress condition (*relative stress* [111]) is generated inside the person's stress response system or HPA axis system. The relative stress condition also regulates the person to have different working memory retrieval performance according to Lupien et al. [104]. During the middle-level stress arousal condition, the working memory retrieval performance condition is ideal for the robot partner to generate new intuition for the unknown environment. The main reason is during middle-level stress arousal condition, the robot partner is *not too challenging* and it has the highest working memory retrieval performance to construct a new intuition or new idea dynamically to solve the given problems in the environment. The environment's conditions are still error tolerance towards the robot partner's new intuition creation behaviours. In other words, the middle-level stress conditions are the ideal conditions to reduce the *cognitive load* [165] for the working memory processing with *heuristic techniques* [134, 149, 176]. Next, we will discuss the implementation of such behaviours into robot partner for human-robot communication application.

7.7 The Development of Robot's Spiking Reflective Processing Modules

The understanding of human's spiking reflective processing (section 6.3) or heuristic mechanism in previous Chapter 6 inspires the development of biological stress-inspired cognitive intelligence with spiking reflective processing mechanism for the robot partner response during ambiguous environment context information. Conversely, a human's physiological spiking reflective processing mechanism is not the same from the robot partner's software-based spiking reflective processing system. Thus, computational spiking reflective processing system simplifications and abstractions are required for a real-time human-robot interaction application. In summary, the assumption is that the fundamental of stress-based spiking reflective processing computation principles are the same for both human and robot partner; however the robot partner's software-based spiking reflective processing needed many simplifications and abstractions. Hence, as discussed in section 2.6, various computation approaches such as evolutionary computational optimisation methods (subsection 2.6.6), neural network models (subsection 2.6.1) and other computational models can be utilised to realise the development of the reflective processing (new intuition creation or heuristic) behaviour for the robot partner.

The following subsections are the robot partner's modules for the human-robot communication experiment:

7.7.1 Image Detection Module

The robot partner captures the environment's visual raw data by its front facing camera image input from the NAO humanoid robot's head. The camera's image input is a 640×480 dimension of RGB pixels that act as the raw visual data sensing for the robot partner's spiking reflective processing model. The camera's image pixels are then repeatedly interpreted by Google images `https://images.google.com/` for image concept detection in raw data input [80, 81]. The role of the Google images search engine is extract information from raw data (pixels) into meaningful representation (concepts) for the robot partner as short-term memory content for spiking reflective processing.

The image captured by the robot's camera will be sent to the Google images search engine as image search to initiate the search. Then, the Google images module will return the image search result page. In the image search result page's HTML source, the image detection module captured the returned of the picture's label texts in the result page and pre-processed it to extract the concept label of the photo.

However, the implementation of the robot's artificial spiking reflective processing mechanism will increase the processing load for the NAO robot partner limited computation hardware capability. The artificial spiking reflective processing created the complex processing cost needs. Hence, the processing load is delegated to server side computer. This implementation design will reduce the power usage needs on the robot body limited battery power supply. Thus, this design is practical for long-hour human-robot communication application.

7.7.2 Sentimental Analysis Module

The sentimental analysis module examines the text sentence from the user's voice to text input, and then the module interprets the sentimental significant that the words represent into confidence level value. Three categories of the confidence levels that are neutral, positive and negative. The output of this module will be the input for stress response system module of the next subsection 7.7.3. The sentimental analysis module for this experiment is a freely available web application `http://sentiment.vivekn.com` by Vivek Narayanan et al. [124]. The result returned from the web page is being used to determine the confidence level value of the sentiment analysis result output of the sentence.

7.7.3 Stress Response System Module

The stress response system module is a component that maintains the artificial homeostatic mechanism of the robot partner. We had discussed the details of human's stress response system in subsection 2.3.1 in Chapter 2. This module balances the artificial stress arousal level of the robot partner by receiving negative and positive stimuli input from sentimental analysis module's output. Positive stimuli will reduce the robot partner's stress level. On the other hand, negative stimuli will increase its stress level. The changes of robot partner's stress arousal level have an influence to its Spiking Reflective Processing Dynamic Bacterial Memetic Algorithm (SRPDBMA) (Section 7.8) spiking reflective processing on working memory. Furthermore, if no further stimuli introduced to this module, the robot partner's stress arousal level will gradually decline as to simulate artificial stress hormone dissolved in the robot partner's stress response system.

7.7.4 Engagement Engine Module

The engagement engine module is a set of predefined conversation dialogue to facilitate the initial engagement of human-robot communication. This module will enable the robot partner to react pro-actively with the user and break-the-ice for any unease feelings from the user that resulted from the first communication experience with a robot partner. For example, the robot partner introduces itself at the start, and then it will initiate questions to the user that related to 3F (friend, family and food) to increase engagement with the user.

7.8 Spiking Reflective Processing Dynamic Bacterial Memetic Algorithm

The proposed spiking reflective processing model (section 6.3) for the robot partner integrates the evolutionary computation and Spiking Neural Network (SNN) techniques to simulate the human spiking reflective processing model's behaviour as discussed in Chapter 6. The Figure 7.3 the proposed SNN framework where the image on the top left is the simplified SNN architecture. The top right corner of the diagram is the overall structure of the SNN as mapped to the robot partner's working memory. Figure 7.3 is the robot partner working memory optimisation with the Spiking Reflective Processing Dynamic Bacterial Memetic Algorithm (SRPDBMA) approach.

In this chapter the proposed method is improved by the static evolutionary computation strategy known as the Bacterial Memetic Algorithm (BMA) by Botzheim et al. [21]. The initial BMA approach captures the bacterial genetic evolution phenomenon as an evolution computation optimisation strategy. Furthermore, as explained in Chapter 4, the proposed method improves the BMA's gene transfer operator with the *Dynamic Programming Gene Transfer (DPGT)* operator [168]. Next, the proposed approach also incorporates the *Average Edit Distance Bacterial Mutation (AEDBM)* operator [167] as an improvement to the initial bacterial mutation operator in the BMA approach. In Chapter 5, these operators were implemented for the robot partner's dynamic working memory optimisation named as Dynamic Bacterial Memetic Algorithm (DBMA) [170].

Later in this chapter, a novel approach to the robot partner working memory spiking reflective processing or heuristic [134, 149, 176] mechanism processing algorithm and dynamic optimisation features are introduced. We named this novel optimisation approach as *Spiking Reflective Processing Dynamic Bacterial Memetic Algorithm (SRPDBMA)*. For the encoding representation of the proposed SRPDBMA approach, the robot partner's working memory is a strings table representing the whole optimisation bacterial population (Figure 7.3). Each row in the robot partner's working memory strings table is represented as a bacterium individual, while, the gene information of the bacterium individual's chromosome represented by each column cell of the working memory row.

In summary, bacterial evolution generation is a type of continuous optimisation of the robot partner's working memory. The term continuous means that optimisation performance may not be required immediately after the environment has changed. However, the working memory will be much optimised towards the intention after a certain time duration. Such behaviour is an important feature for continuous optimisation where the continuous optimisation simulates the robot partner's working memory's flexible adaptation to a new environment, the continuous optimisation gradually adapt to the new environment or revert to the previous working memory state.

The proposed SRPDBMA approach as stated in Algorithm 11 is a spiking reflective processing (new intuition generation) mechanism based on a stochastic optimi-

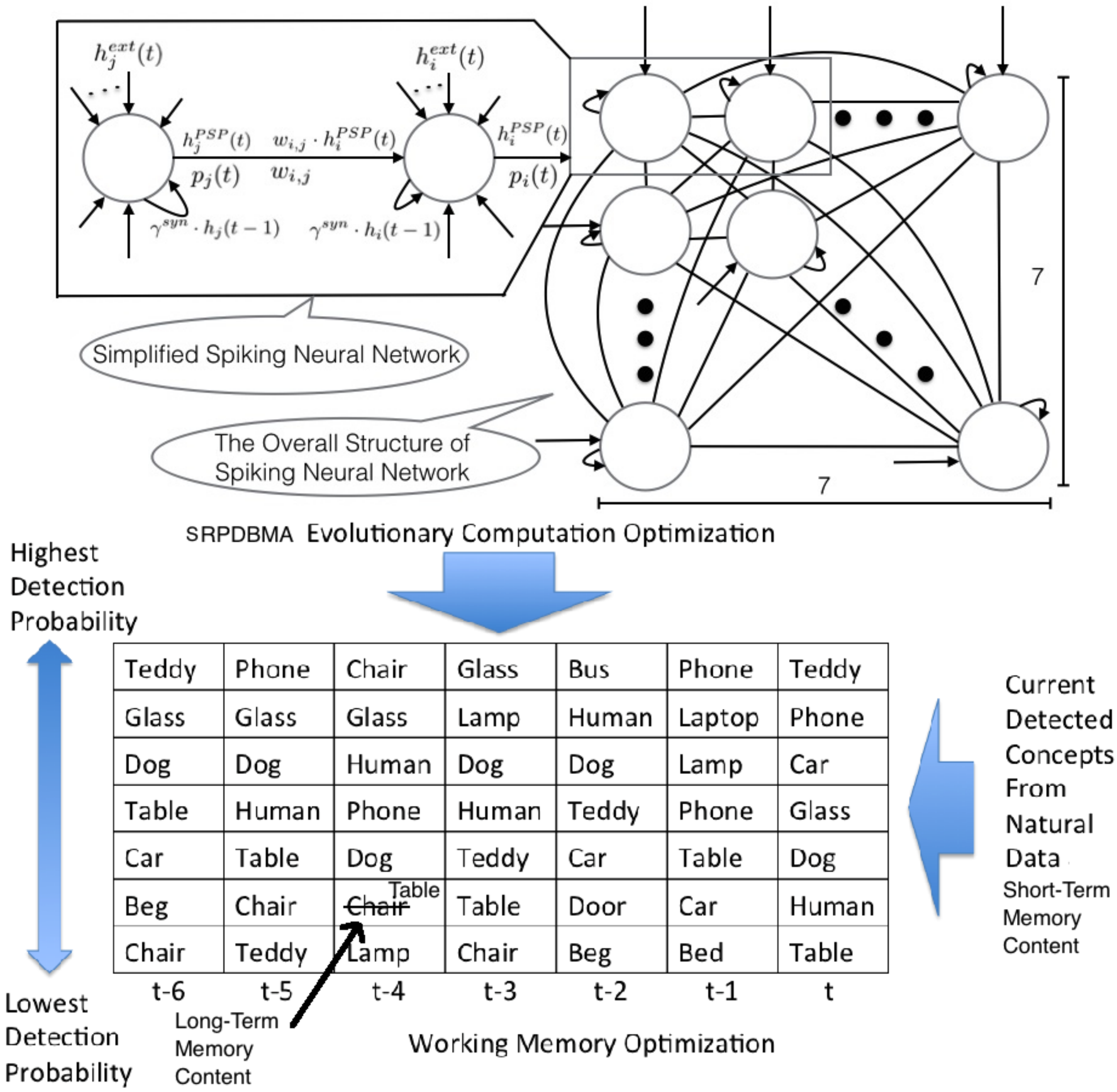

Figure 7.3: The Relationship between the Spiking Neural Network Architecture with the Robot Partner Working Memory Optimisation.

sation algorithm that combines global and local search operators for optimising the robot partner's working memory. The proposed SRPDBMA approach is designed to find a partial-optimal solution in the robot partner's working memory at given time t. For global search operators in SRPDBMA, two improved operators are integrated into the SRPDBMA approach from the original BMA approach [21], i.e. the AEDBM operator and DPGT [168] operator.

Initially, the proposed SRPDBMA approach updates the robot partner's working memory with new visual concepts detection from the image detection module at subsection 7.7.1 [80, 81]. Secondly, an SNN based approach is implemented in the spiking reflective processing algorithm as mentioned in section 7.8. The spiking reflective processing algorithm will decide the robot partner's condition as to whether it is eligible for creating a new intuition.

The proposed SRPDBMA approach will continue to iterate a loop until N_{gen} generations (stop condition). Then, for the bacterial evolution loop the AEDBM operator [167] is implemented to improve the bacterium's chromosome. Subsequently, the Open CyC [98] human expert knowledge based inference system is applied for the local search operator. Open CyC [98] represents the behaviour of long-term memory content referenced into the working memory. The main feature of the local search operator is optimising the bacterium's chromosome information to a more specific or local optimum. Lastly, the DPGT operator permits the transfer of chromosome information among bacterial individuals in the bacterial population (robot partner's working memory). When the bacterial evolution ends at N_{gen}, then the algorithm exits SRPDBMA and it starts the image concept detection process [80, 81] (subsection 7.7.1) again. The AEDBM operator [167] duplicates clones of itself with an N_c number total of clones from a bacterial individual selected in the population.

The NAO robot partner is the thin-client interface for human-robot interaction with the human test subject. The AEDBM operator [167] is an improvement from the previous bacterial mutation operator [21] by comparing the clones' gene similarity elements with the average edit distances before assigning the gene information to other clones. Then for the local search operator, the Open Cyc [98] human expert general knowledge inference system is used to optimise a selected concept to a more accurate concept. Open Cyc [98] system enables reference memory referenced into the working memory as discussed in section 7.6. As an example, an individual bacterium (row) is selected in the working memory based on the probability that exceeds τ value. Then, a stored image concept string "Bus" in the working memory cell is chosen based on the probability percentage that exceeds α. Next, the Open Cyc framework [98] will

Algorithm 11 Spiking Reflective Processing Dynamic Bacterial Memetic Algorithm

procedure SRPDBMA
  Update Working Memory X as
    bacterial population
  The Spiking Reflective Processing Algorithm
  $generation \leftarrow 0$
  while $generation \neq N_{gen}$ **do**
    AEDBM applied to each bacterium
    Local search for each baterium
    DPGT applied for the population
    $generation \leftarrow generation + 1$

optimise the concept “Bus” to a subclass concept that is more explicit than the bus concepts like “School Bus”, “Public Bus” and “Double-Decker Bus”. The configuration settings of threshold τ and α are the local search operator settings.

The last step in the SRPDBMA approach is where the DPGT operator [168] for horizontal gene transfers operations between bacterium individuals. The performing individuals gene information will be transferred to the inferior ones. The sorted fitness values of bacterial population will divide the whole population into two groups. The DPGT operator [168] compares the similarity of the source and destination bacterium gene elements in term of edit distance difference before transmitting the gene information to the target bacterium gene. This comparison step is needed because it is to reduce the inbreeding depression [79] effects of the population. The N_{inf} parameter is the infection frequency for the DPGT algorithm.

7.9 Spiking Reflective Processing Algorithm

Figure 7.3 showing the proposed spiking reflective processing algorithm (section 6.3) begins by processing the Spiking Neural Network (SNN) model [61] external input influences $h_j^{ext}(t)$ assignment during time t with the Equation 7.1.

$$h_j^{ext}(t) = \zeta \cdot \frac{1}{1 + min_{ed}(a, b)} \cdot \rho_j, \tag{7.1}$$

The input rate of the external input to the SNN is $\zeta = 1$ and ρ_j denote the concept detection probability of the j concept. The minimum edit distance between concept strings a and b is defined as $min_{ed}(a, b)$. Each SNN node represents the seven times seven matrix of the robot partner’s working memory as illustrated in Figure 7.3.

The equation $g(x) = \exp(-\frac{(h_{gc}-\mu)^2}{2\sigma^2})$ defines the total number of rows to be optimised by the SRPDBMA. Next, the sentimental analysis module (subsection 7.7.2) will trigger increase and decrease changes of h_{gc} stress arousal level. Furthermore, let's define the internal state $h_i(t)$ of the i-th SNN's membrane potential at the different time t with a hyperbolic tangent function of $h_i^{syn}(t) + h_i^{ext}(t) + h_i^{ref}(t)$. The primary reason for utilising the hyperbolic tangent function is to prevent the over bursting of SNN fires.

Besides, the $h_i^{syn}(t)$ are the pulses from other connected neurones' outputs in a fully connected SNN at time t computed as:

$$h_j^{syn}(t) = \gamma^{syn} \cdot h_i(t-1) \sum_{j=1, j\neq i}^{N} w_{j,i}.h_j^{PSP}(t-1), \tag{7.2}$$

Where the temporal discount rate is the γ^{syn} of the internal state, h_i. The Post-Synaptic Potential (PSP) [61] is denoted by $h_j^{PSP}(t)$ is transmitted from the jth neurone at time t. Then, the total number of spiking neurones is set at $N = 7 \times 7$. *Post-Synaptic Potential* is the response from the postsynaptic neurone to a presynaptic action potential.

Figure 7.3 on its left illustrates the postsynaptic potential in the simplified structure of two spiking neurones j and i. Subsequently, the jth neurone is the sender (presynaptic) spiking neurone and the ith neurone is the receiver (postsynaptic) neurone, $w_{i,j}$ is the weight between these spiking neurones. Then $h_i^{ref}(t)$ denotes the refractoriness of the neurone at time t. The refractoriness refers to a spiking neurone after fired, and then it needs to reduce the internal condition of the fired spiking neurone to avoid continuous firing. If the internal state of the ith spiking neurone exceeds a predefined θ threshold level, a pulse is generated, the $h_i^{PSP}(t)$ value is 1, and a positive value of R will subtract $h_i^{ref}(t)$.

Also, the values of $h_i^{PSP}(t)$ and $h_i^{ref}(t)$ will be discounted by γ^{PSP} and γ^{ref} discount rates correspondingly from their previous values at time $t-1$. The proposed reflective processing algorithm returns a Boolean value whether a new intuition creation is needed or not for the robot partner at that particular moment.

7.10 Experimental Settings

7.10.1 Hardware and Software Settings

A PC desktop computer with 2.8 GHz Intel Core i7 processor with 16 GB 1600 MHz DDR3 RAM executed the modules as discussed in section 7.7. We implemented these modules in Ubuntu 14.04 operating system. Furthermore, we used Python language version 2.7.6 application environment and the Open Cyc 4.0 framework [98] is interfaced with Java version 1.7.0 environment to implement the proposed SRPDBMA approach. We developed the modules (section 7.7) with Robot Operating System (ROS) version Indigo for middle layer inter-modules communication framework. We selected the LAN connection because of its lack of latency connection between the PCs, NAO robot partner and the Internet. The NAO robot partner version Next Gen is a thin-client interface for human-robot interaction with the human test subject.

7.10.2 Parameter Settings

Next, N_{gen} denotes as the total bacterial generations and it is 10. Besides, the total number of bacteria is defined as N_{bac} and is set at 5 and then N_c, the total number of clones, is configured at 5. Subsequently, N_{inf} number of infections is set at 5; τ local search probability threshold is 0.95 and α assignment probability is 0.9. Then, N_{search} maximum search count is set at 5. For the stress settings, the mean is set at $\mu = 0.5$ and a standard deviation is set at $\sigma = 4$ for the Gaussian curve of the stress arousal and working memory retrieval performance relationship.

7.10.3 Physical Environment Settings

We conducted the experiment in focus group discussion room at Monash University Malaysia Sunway Campus. The experiment environment setting is similar to a living room environment with comfortable sofa and table setting (Figure 7.4-7.7). The focus group discussion room has multiple high definition video recording devices. All human-robot communication activities in the experiment were video recorded for this research purpose only.

The participants are randomly selected in Monash University Malaysia Sunway Campus to participate in this experiment. All participants had given an explanatory statement and consent form to read (Appendix A.16). After the student investigator explained the experiment conditions to the participant, if the participant agreed to participate in this experiment, he or she must sign the consent form before the experiment can begin. Then, the participant need to fill in the questionnaire form (Appendix A.17) for before the conversation and after the conversation with the NAO robot partner.

The participants conversation topic should not limit to any particular subject during their human-robot interaction with the robot partner. The reason is the participants feedback should be as realistic and natural as possible to be represented without any constraints attached to the conversation topic. Therefore, the participants are free to express their natural views towards the robot partner in our experiment. Furthermore, the survey questions (Appendix A.17) are designed to capture the participants natural (non-restrictive) views towards robot partner.

Figure 7.4: One of the examples of an older participant engaging in human-robot interaction experiment in focus group discussion room at Monash University Malaysia Sunway Campus.

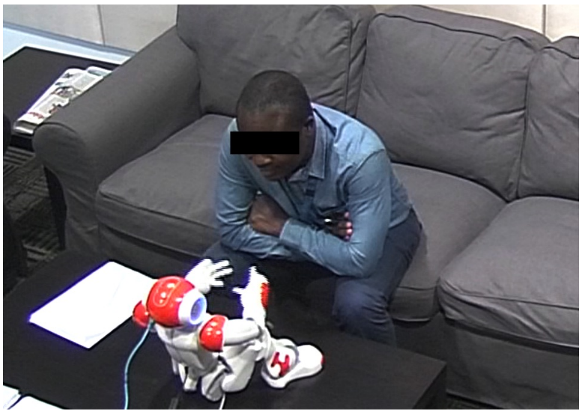

Figure 7.5: One of the examples of a Monash lecturer staff participant engaging in human-robot interaction experiment in focus group discussion room at Monash University Malaysia Sunway Campus.

Figure 7.6: One of the examples of a Ph.D. student participant engaging in human-robot interaction experiment in focus group discussion room at Monash University Malaysia Sunway Campus.

Figure 7.7: One of the examples of an undergraduate student participant engaging in human-robot interaction experiment in focus group discussion room at Monash University Malaysia Sunway Campus.

7.11 Experimental Results

The attachment in the appendix section of this thesis A.18 is the captured raw data for human-robot communication questionnaire. The following bar charts and crosstabulations are the analysis of the raw data. We use IBM's SPSS statistics version 20 software for analysis of these gathered raw data.

The reason we choose the crosstabulation bar chart type to describe our finding is because it explain the differences between two variables with visual information effectively. Furthermore, crosstabulation bar chart type is build into the IBM's SPSS statistics version 20 software as the standard comparison chart. The horizontal axis belongs to the *before* human-robot interaction response distribution. Next, the coloured bars of vertical axis consist of *after* human-robot interaction response distribution. We can detect the positive or negative changes from the bar charts by analysing for the transitions from *before (label)* to *after (coloured bar)*.

We used Kendall and Spearman instead of Pearson correlation coefficient to analyse our gathered survey data (Table 7.2 and Table 7.3). The reason is we use Kendall and Spearman correlation coefficient because we do not remove the data outliers and the data is not a continuous data type (single selection on multiple answers). Therefore, Kendall and Spearman correlation coefficient are designed to analyse correctly the non-perfect normal distribution population of our captured experimental data.

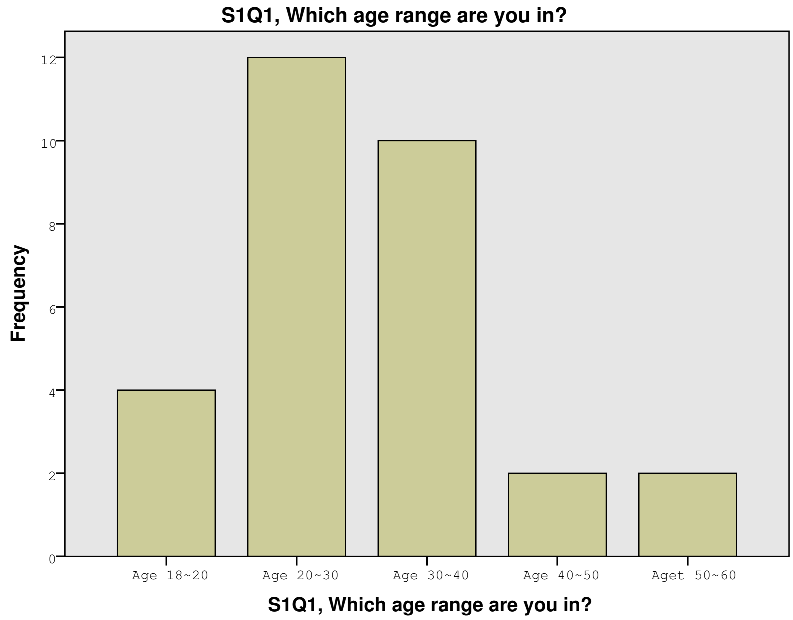

Figure 7.8: Section 1 question 1 bar chart: Which age range are you in?

Figure 7.9: Section 1 question 2 bar chart: What is your gender?

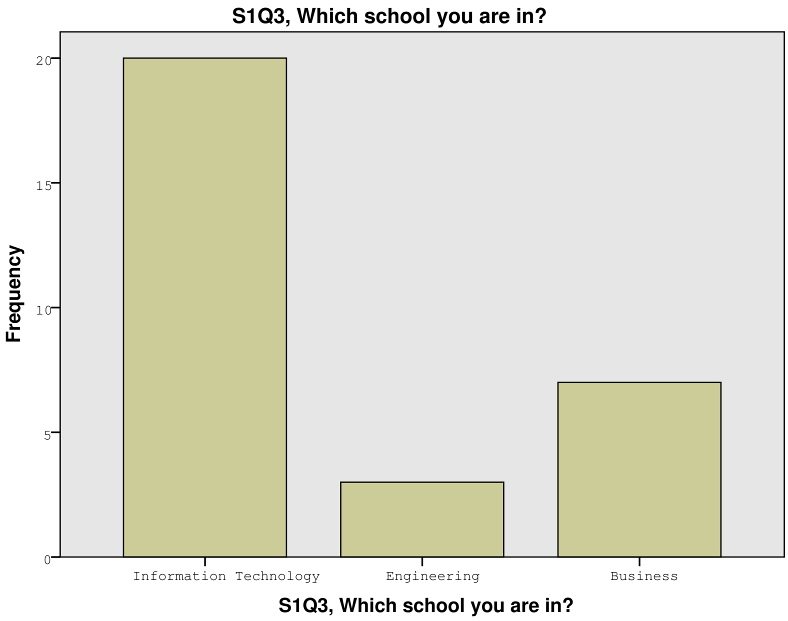

Figure 7.10: Section 1 question 3 bar chart: Which school you are in?

S2Q1, I feel calm. * S5Q1, I feel calm. Crosstabulation

Count

		S5Q1, I feel calm.			
		Very much	Moderately	Some what	Total
S2Q1, I feel calm.	Very much	13	4	0	17
	Moderately	4	3	2	9
	Some what	0	2	2	4
Total		17	9	4	30

Figure 7.11: Section 2 question 1 (before) vs section 5 question 1 (after) crosstabulation: I feel calm.

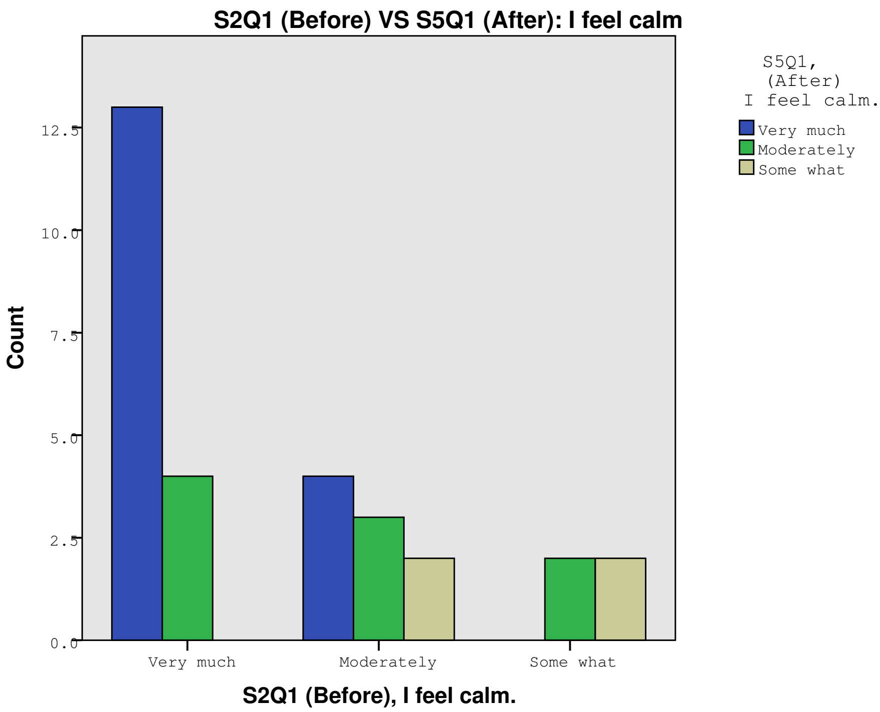

Figure 7.12: Section 2 question 1 (before) vs section 5 question 1 (after) bar chart: I feel calm.

S2Q2, I am tense. * S5Q2, I am tense Crosstabulation

Count

		S5Q2, I am tense				Total
		Very much	Moderately	Some what	No at all	
S2Q2, I am tense.	Moderately	0	2	2	1	5
	Some what	1	1	4	2	8
	Not at all	0	3	1	13	17
Total		1	6	7	16	30

Figure 7.13: Section 2 question 2 (before) vs section 5 question 2 (after) crosstabulation: I am tense.

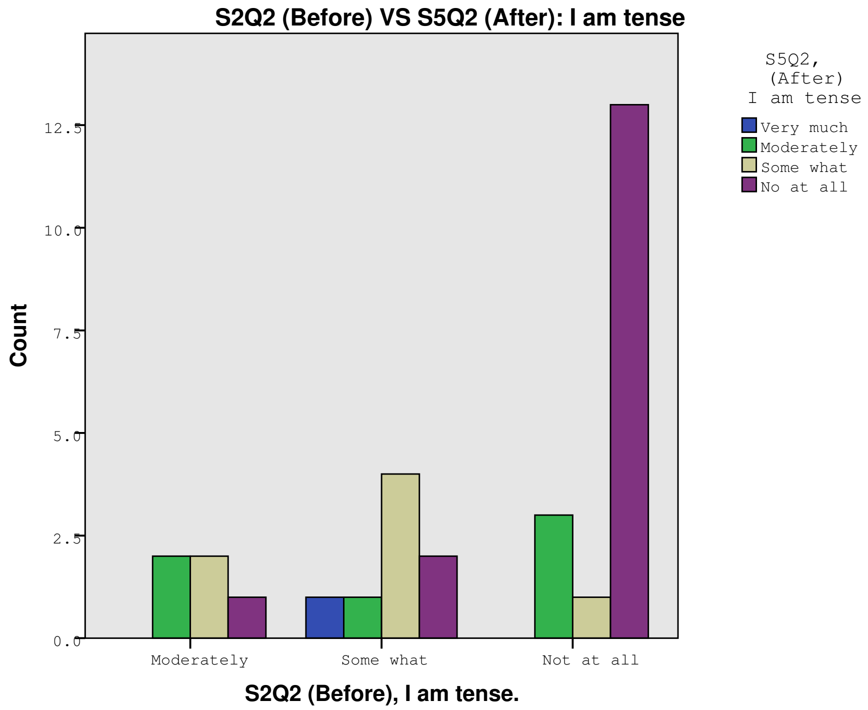

Figure 7.14: Section 2 question 2 (before) vs section 5 question 2 (after) bar chart: I am tense.

S2Q3, I feel upset. * S5Q3, I feel upset. Crosstabulation

Count

		S5Q3, I feel upset.			Total
		Moderately	Some what	No at all	
S2Q3, I feel upset.	Moderately	0	0	1	1
	Some what	0	0	1	1
	Not at all	2	2	24	28
Total		2	2	26	30

Figure 7.15: Section 2 question 3 (before) vs section 5 question 3 (after) crosstabulation: I feel upset.

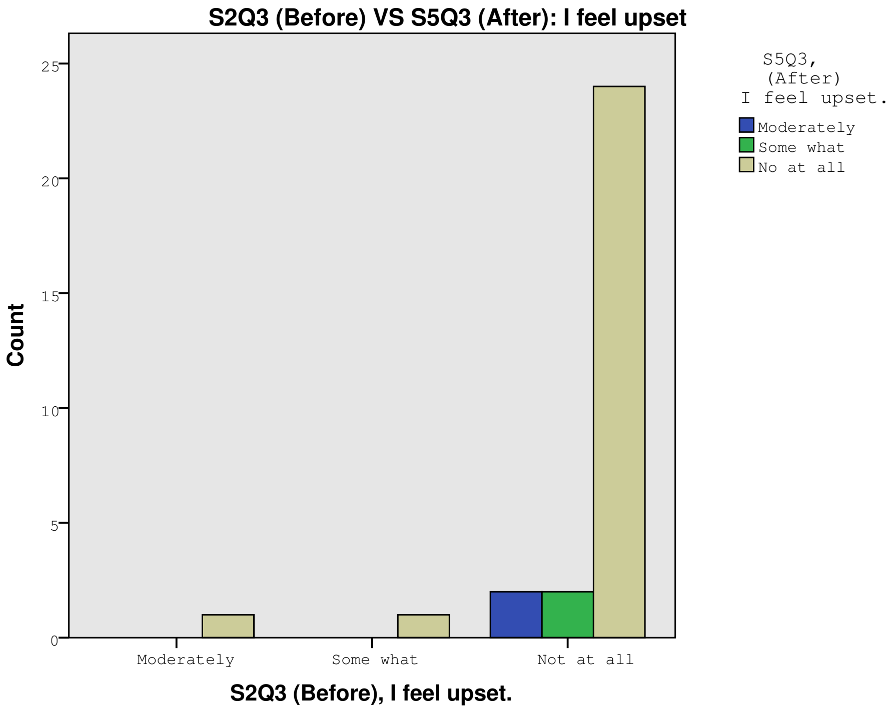

Figure 7.16: Section 2 question 3 (before) vs section 5 question 3 (after) bar chart: I feel upset.

S2Q4, I am relaxed. * S5Q4, I am relaxed. Crosstabulation

Count

		S5Q4, I am relaxed.				
		Very much	Moderately	Some what	No at all	Total
S2Q4, I am relaxed.	Very much	9	1	1	0	11
	Moderately	3	4	3	0	10
	Some what	2	3	3	0	8
	Not at all	0	0	0	1	1
Total		14	8	7	1	30

Figure 7.17: Section 2 question 4 (before) vs section 5 question 4 (after) crosstabulation: I am relaxed.

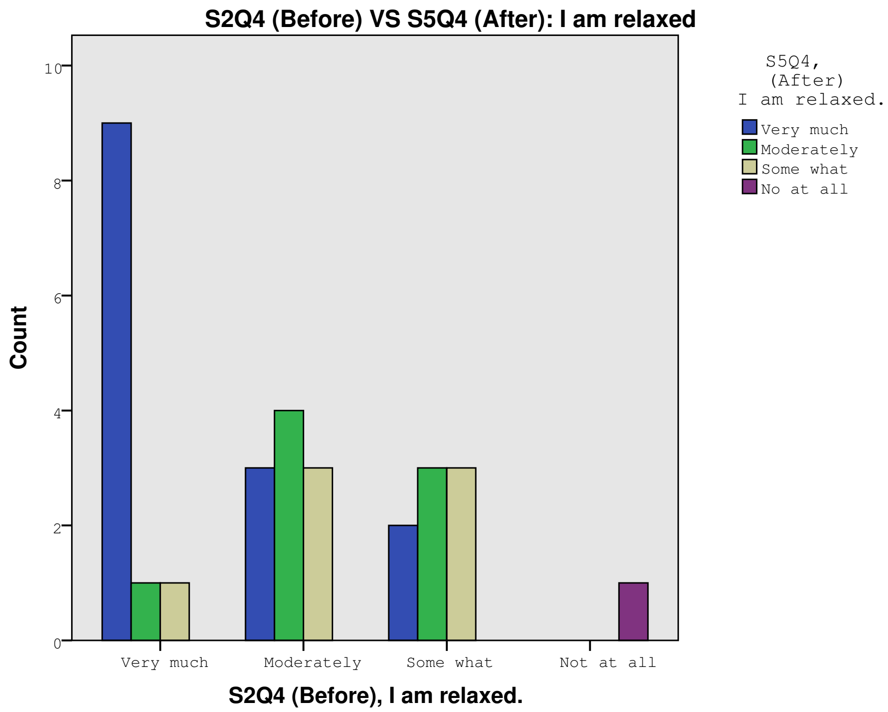

Figure 7.18: Section 2 question 4 (before) vs section 5 question 4 (after) bar chart: I am relaxed.

S2Q5, I feel content. * S5Q5, I feel content. Crosstabulation

Count

		S5Q5, I feel content.				
		Very much	Moderately	Some what	No at all	Total
S2Q5, I feel content.	Very much	9	3	0	0	12
	Moderately	2	7	3	0	12
	Some what	0	4	0	0	4
	Not at all	0	0	1	1	2
Total		11	14	4	1	30

Figure 7.19: Section 2 question 5 (before) vs section 5 question 5 (after) crosstabulation: I feel content.

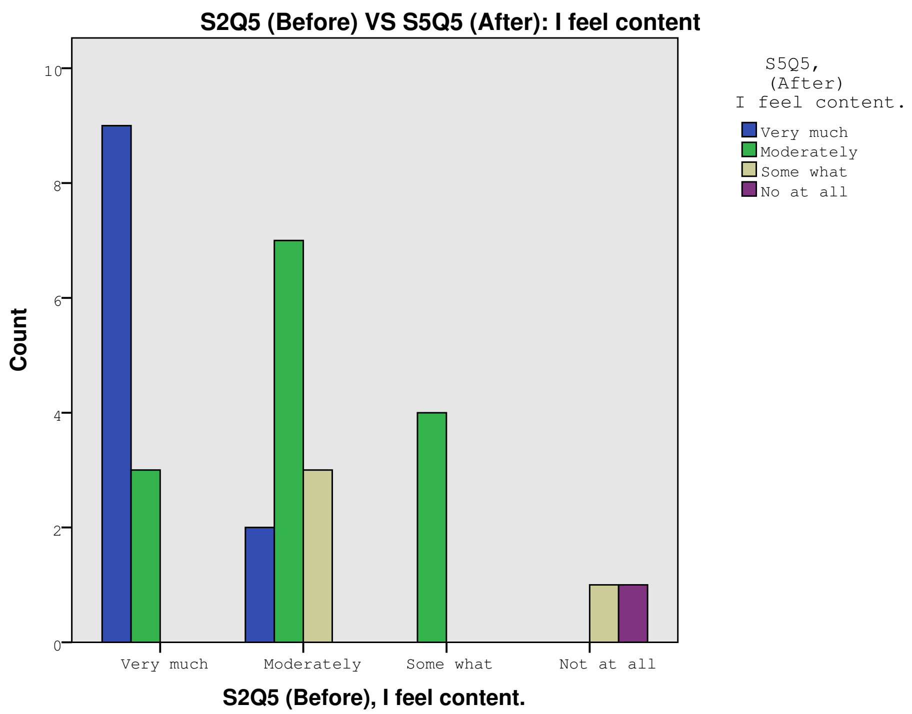

Figure 7.20: Section 2 question 5 (before) vs section 5 question 5 (after) bar chart: I feel content.

S2Q6, I am worried. * S5Q6, I am worried. Crosstabulation

Count

		S5Q6, I am worried.			Total
		Moderately	Some what	No at all	
S2Q6, I am worried.	Moderately	1	2	2	5
	Some what	0	1	3	4
	Not at all	1	2	18	21
Total		2	5	23	30

Figure 7.21: Section 2 question 6 (before) vs section 5 question 6 (after) crosstabulation: I am worried.

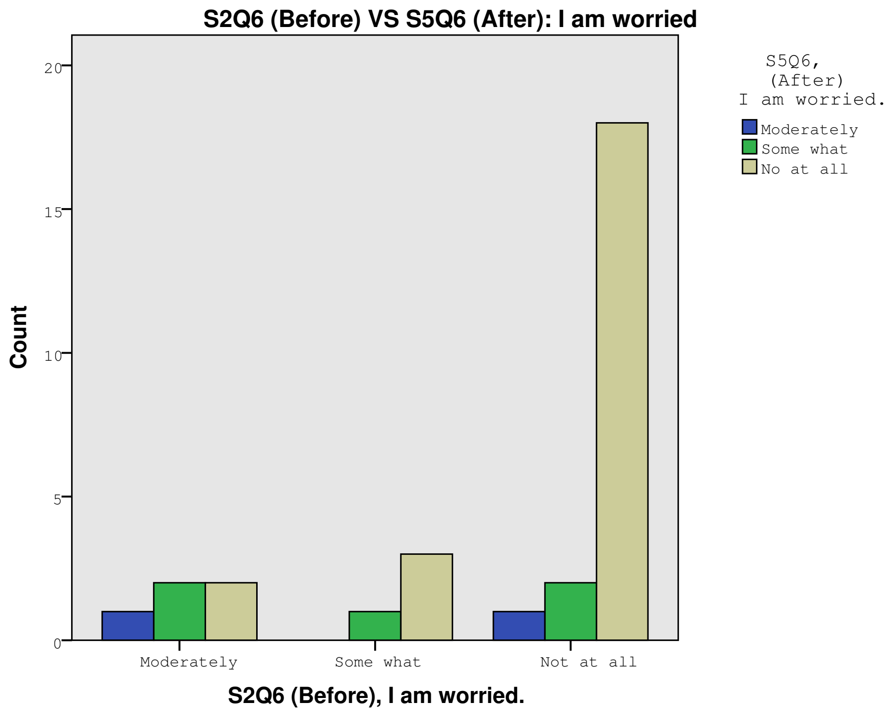

Figure 7.22: Section 2 question 6 (before) vs section 5 question 6 (after) bar chart: I am worried.

	S4Q1	S4Q2	S4Q3	S4Q4	S4Q5	S4Q6	S4Q7	S4Q8	S4Q9	S4Q10	S4Q11	S4Q12	Total
Strongly agree	15	18	2	2	3	3	1	13	4	10	3	1	75
Agree	11	9	16	11	15	8	24	16	11	16	12	15	164
Neutral	3	2	9	8	8	13	4	1	13	4	9	8	82
Disagree	1	0	3	9	4	6	1	0	1	0	5	4	34
Strongly disagree	0	1	0	0	0	0	0	0	1	0	1	2	5

Table 7.1: The Summary of Section 4 from Question 1 to 12.

Before negative attitude toward situations of interaction with robots. * After negative attitude toward situations of interaction with robots. Crosstabulation

Count

		After negative attitude toward situations of interaction with robots.				
		Slightly agree	Feel exactly neutral	Slightly disagree	Strongly disagree	Total
Before negative attitude toward situations of interaction with robots.	Feel exactly neutral	1	2	4	0	7
	Slightly disagree	0	4	10	4	18
	Strongly disagree	0	0	2	3	5
Total		1	6	16	7	30

Figure 7.23: Group 1 crosstabulation: Before and after comparison of negative attitude toward situations of interaction with robots.

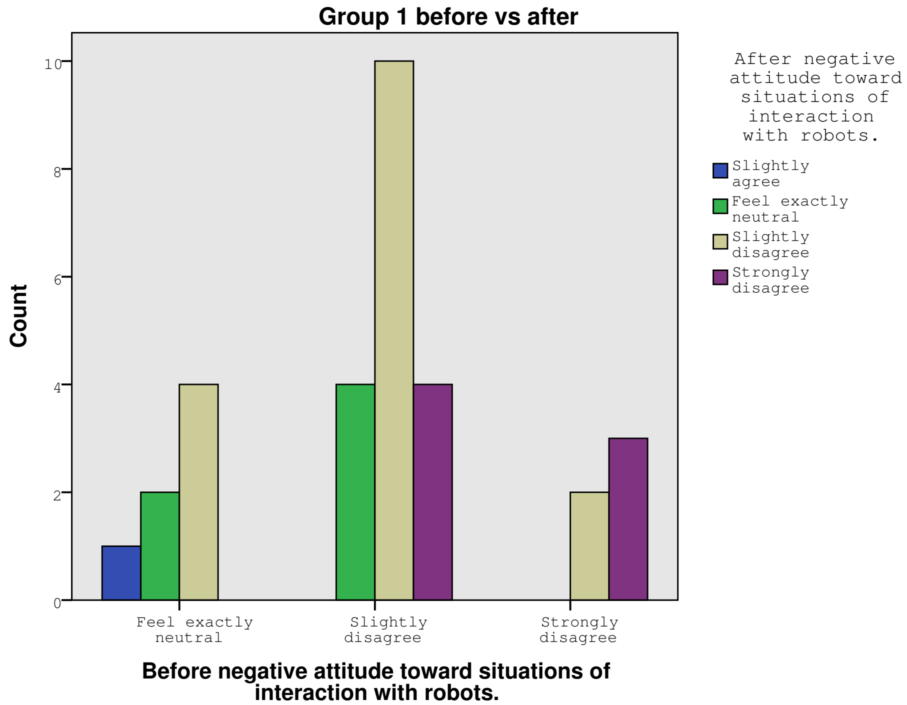

Figure 7.24: Group 1 bar chart: Before and after comparison of negative attitude toward situations of interaction with robots.

Before negative attitude toward social influence of robots. * After negative attitude toward social influence of robots. Crosstabulation

Count

		After negative attitude toward social influence of robots.				
		Strongly agree	Slightly agree	Feel exactly neutral	Slightly disagree	Total
Before negative attitude toward social influence of robots.	Strongly agree	1	0	0	0	1
	Slightly agree	0	4	3	0	7
	Feel exactly neutral	0	4	5	3	12
	Slightly disagree	0	0	3	7	10
Total		1	8	11	10	30

Figure 7.25: Group 2 crosstabulation: Before and after comparison of negative attitude toward the social influence of robots.

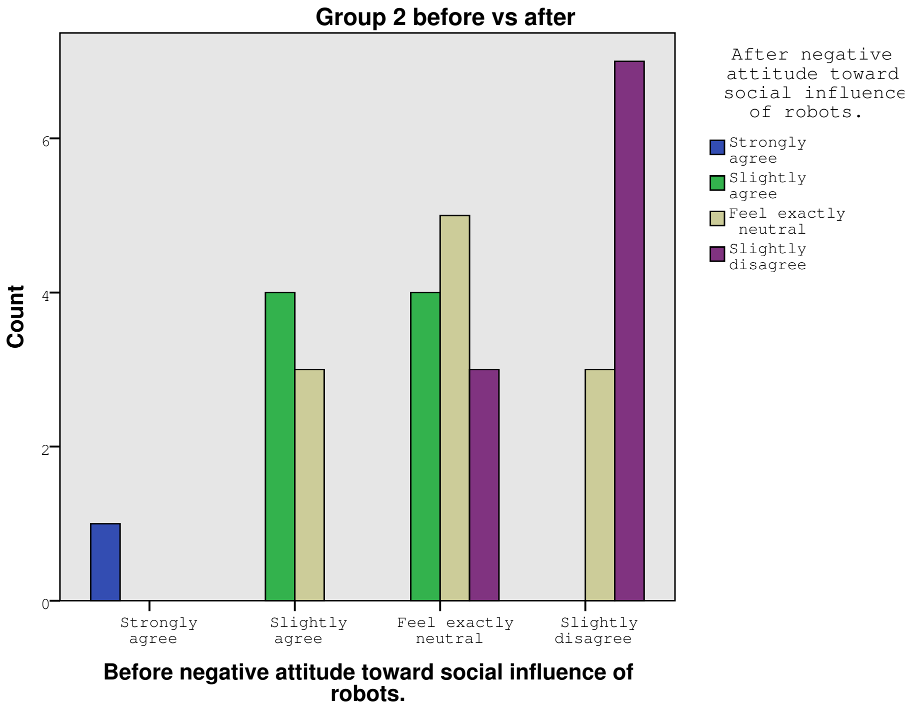

Figure 7.26: Group 2 bar chart: Before and after comparison of negative attitude toward the social influence of robots.

Before negative attitude toward emotions in interaction with robots * After negative attitude toward emotions in interaction with robots Crosstabulation

Count

		After negative attitude toward emotions in interaction with robots					
		Strongly agree	Slightly agree	Feel exactly neutral	Slightly disagree	Strongly disagree	Total
Before negative attitude toward emotions in interaction with robots	Strongly agree	1	0	0	0	0	1
	Slightly agree	0	0	0	1	0	1
	Feel exactly neutral	0	3	3	6	0	12
	Slightly disagree	0	0	2	13	1	16
Total		1	3	5	20	1	30

Figure 7.27: Group 3 crosstabulation: Before and after comparison of negative attitude toward emotions in interaction with robots.

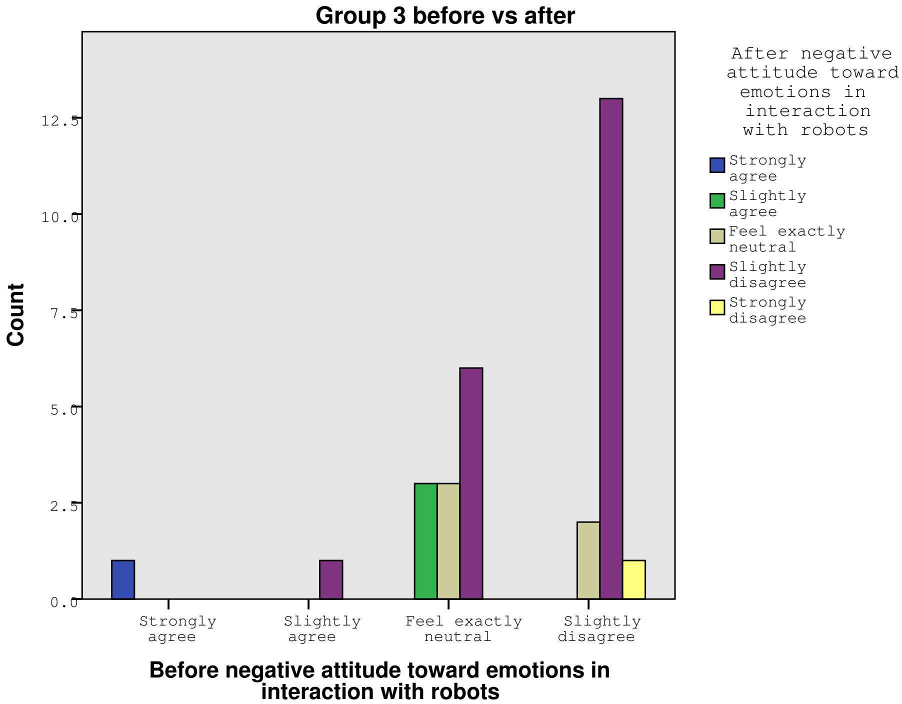

Figure 7.28: Group 3 bar chart: Before and after comparison of negative attitude toward emotions in interaction with robots.

7.12 Analysis of Results

7.12.1 Frequency Analysis

In this experiment, the majority of our participants are undergraduate students in Monash University Malaysia, but we also manage to obtain four older participants that ranged from age 40 to 60 years old (Figure 7.8). The participants' gender demographic is mostly balanced however slightly skewed towards male (Figure 7.9). The majority of the test subjects are from the school of information technology (Figure 7.10). Still, we managed to obtain seven students from the school of business and three students from the school of engineering.

The human-robot communication questionnaire (Appendix A.17) is designed to capture the participant states before and after of the human-robot communication experiment. The six-item State-Trait Anxiety Inventory (STAI) test [110] is used to evaluate participant's emotions states before and after having conversations with the robot partner. The short form of six-item STAI that utilised in this experiment is the smaller version of Spielberger's full 40 items STAI test [153].

The STAI comparison bar chart and crosstabulation (Figure 7.12 and Figure 7.11) on question 1 (I feel calm), it does not reveal any significant changes before and after the experiment, however overall the human-robot communication experiment enables the participant to feel *very much calm* in the whole process. The bar chart shows a positive result as it empirically indicated that our proposed robot partner approach provides the comfortable feelings to the users that could potential improves the human-robot communication engagement. Next, the STAI comparison question 2 (I am tense), the bar chart and crosstabulation (Figure 7.14 and Figure 7.13) indicated positive result that the majority test subjects *do not feel tense at all* before and after the conversation with the robot partner. The bar chart supports our research objective that the robot partner approach is acceptable because it does not cause uneasy feelings to the users. Furthermore, the STAI comparison question 3 (I feel upset), the bar chart and crosstabulation (Figure 7.16 and Figure 7.15) indicated positive result from the majority of the test subjects are *not angry*. However, some minority of the test subjects are slightly skewed towards upset after the human-robot communication experiment. According to the test subjects explanations in the questionnaire section 4 question 14 (appendix A.18), most of the test subjects are upset about the robot partner's slow reply speed. However, the robot partner's reply speed are limited by voice-to-text recognition technology that is out of our research scope. Next, the STAI comparison question 4 (I am relaxed), the bar chart and crosstabulation (Figure 7.18 and Figure 7.17) shows positive result that the test subjects are *very much relaxed* in after their conversation with the robot partner. This relaxed feeling could also potentially improve the human-robot communication engagement. Furthermore, the STAI comparison question 5 (I feel content), the bar chart and crosstabulation (Figure 7.20 and Figure 7.19) revealed the positive result of test subjects are *very much content* with the human-robot communication experiment. Finally, the STAI comparison question 6 (I am worried), the bar chart and crosstabulation (Figure 7.22 and Figure 7.21) indicate positive result that the test participants are *not worried at all*. Furthermore, the diagram also revealed significant improvement after the human-robot communication experiment.

The Negative Attitude Toward Robots Scale (NARS) [129] is the measurement of test participants negative attitude towards a robot that tested with 14 survey questions in three groups (See [129] for the question's category). The bar chart and crosstabulation (Figure 7.24 and Figure 7.23) described the first group of questions that tested negative attitude toward situations of interaction with robots; this graph had revealed the positive result by test subjects that shows better perceptions of human-robot interaction after the experiment. The bar chart and crosstabulation (Figure 7.26 and Figure 7.25) explained the second group of questions that is the negative attitude towards the social influence of robots. Although this graph showed slightly negative results, however according to the test subjects (Appendix A.18) 19 out of 30 participants, do not have experience played with the robot before. Therefore, the participants may not have confidence in robot social influence towards human society. Finally, the bar chart and crosstabulation (Figure 7.28 and Figure 7.27) is the third group of questions that is a negative attitude toward emotions in communication with robots. After the human-robot communication experiment, the graph (Figure 7.28) showed positive result that the test subjects attitude towards emotion were improved. The Negative Attitude Toward Robots Scale (NARS) [129] overall experimental results answered our research question (research question 3 (RQ3) in subsection 1.7.3) that our proposed model can reduce the participants negative attitude towards the robot. Therefore, the proposed model is able to improve the state-of-the-art cognitive intelligence for robot partners by applying biological stress principles.

The Table 7.1 S4Q1 column, shows that the test subjects *strongly agree* that they currently have good companionship from their family and friends. Next, the Table 7.1 S4Q2 column indicated the majority of the test subjects like technologies. Then, the Table 7.1 S4Q3 column shows the majority of the test subjects noticed that the robot partner pays attentions to them quickly. Meanwhile, the Table 7.1 S4Q4 column revealed the test subject feel that he or she think that the robot partner is aware of its environment. The diagram is significant evidence to support our proposed spiking reflective processing model that emphasise on environment context information. Furthermore, in Table 7.1 S4Q5 column and S4Q6 column, the participants also think the robot expressed many of its thoughts and ideas, this result is an indicator that the robot can generate its new intuition effectively during the human-robot communication experiment. In addition to that, the Table 7.1 S4Q7 column also pointed out that the human-robot conversation topic is relevant to the certain degree of the environment context information, which these findings support our proposed spiking reflective processing.

Correlations

			Before negative attitude toward situations of interaction with robots.	Before negative attitude toward social influence of robots.	Before negative attitude toward emotions in interaction with robots	After negative attitude toward situations of interaction with robots.	After negative attitude toward social influence of robots.	After negative attitude toward emotions in interaction with robots
Kendall's tau_b	Before negative attitude toward situations of interaction with robots.	Correlation Coefficient	1.000	.004	.532**	.435**	.065	.249
		Sig. (2-tailed)	.	.983	.002	.010	.697	.141
		N	30	30	30	30	30	30
	Before negative attitude toward social influence of robots.	Correlation Coefficient	.004	1.000	.317	.117	.607**	.407*
		Sig. (2-tailed)	.983	.	.061	.476	.000	.014
		N	30	30	30	30	30	30
	Before negative attitude toward emotions in interaction with robots	Correlation Coefficient	.532**	.317	1.000	.368*	.242	.441*
		Sig. (2-tailed)	.002	.061	.	.031	.151	.010
		N	30	30	30	30	30	30
	After negative attitude toward situations of interaction with robots.	Correlation Coefficient	.435**	.117	.368*	1.000	.335*	.381*
		Sig. (2-tailed)	.010	.476	.031	.	.041	.022
		N	30	30	30	30	30	30
	After negative attitude toward social influence of robots.	Correlation Coefficient	.065	.607**	.242	.335*	1.000	.438**
		Sig. (2-tailed)	.697	.000	.151	.041	.	.008
		N	30	30	30	30	30	30
	After negative attitude toward emotions in interaction with robots	Correlation Coefficient	.249	.407*	.441*	.381*	.438**	1.000
		Sig. (2-tailed)	.141	.014	.010	.022	.008	.
		N	30	30	30	30	30	30

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Table 7.2: Kendall's tau b correlation analysis on Negative Attitude Toward Robots Scale (NARS) results before and after the human-robot conversation experiment.

Correlations

			Before negative attitude toward situations of interaction with robots.	Before negative attitude toward social influence of robots.	Before negative attitude toward emotions in interaction with robots	After negative attitude toward situations of interaction with robots.	After negative attitude toward social influence of robots.	After negative attitude toward emotions in interaction with robots
Spearman's rho	Before negative attitude toward situations of interaction with robots.	Correlation Coefficient	1.000	.005	.582**	.476**	.071	.280
		Sig. (2-tailed)	.	.978	.001	.008	.710	.134
		N	30	30	30	30	30	30
	Before negative attitude toward social influence of robots.	Correlation Coefficient	.005	1.000	.337	.132	.671**	.441*
		Sig. (2-tailed)	.978	.	.069	.487	.000	.015
		N	30	30	30	30	30	30
	Before negative attitude toward emotions in interaction with robots	Correlation Coefficient	.582**	.337	1.000	.402*	.264	.466**
		Sig. (2-tailed)	.001	.069	.	.027	.159	.009
		N	30	30	30	30	30	30
	After negative attitude toward situations of interaction with robots.	Correlation Coefficient	.476**	.132	.402*	1.000	.375*	.419*
		Sig. (2-tailed)	.008	.487	.027	.	.041	.021
		N	30	30	30	30	30	30
	After negative attitude toward social influence of robots.	Correlation Coefficient	.071	.671**	.264	.375*	1.000	.477**
		Sig. (2-tailed)	.710	.000	.159	.041	.	.008
		N	30	30	30	30	30	30
	After negative attitude toward emotions in interaction with robots	Correlation Coefficient	.280	.441*	.466**	.419*	.477**	1.000
		Sig. (2-tailed)	.134	.015	.009	.021	.008	.
		N	30	30	30	30	30	30

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Table 7.3: Spearman's rho correlation analysis on Negative Attitude Toward Robots Scale (NARS) results before and after the human-robot conversation experiment.

The Kendall and Spearman correlation coefficient analysis (Table 7.2 and Table 7.3) indicated many significant correlations in the Negative Attitude Toward Robots Scale (NARS) results. The nine cells at the bottom right (bold font) in these two figures indicated many significant correlations between the three group of questions in NARS result. Furthermore, the overall NARS result showed positive feedback from the participants. Therefore, we conclude that the participants are in consensus about their positive feedback after the human-robot conversation experiment.

The Table 7.1 S4Q8, S4Q10, S4Q11 and S4Q12 columns indicated that the test participants are overall happy with the human-robot conversation with the robot partner. These bar chart's result had answered our research question 3 (RQ3) in subsection 1.7.3 on how our proposed spiking reflective processing model can better social support to the elderly people and other age group population. Furthermore, in the Table 7.1 S4Q9 column. Our proposed model also enable the test participants to be more alert and thus it help increase the mental activity and reduce the risk of mental diseases such as dementia and Alzheimer's disease (as discussed in Chapter 1 subsection 1.2.2).

7.12.2 One-Way ANOVA Analysis: Before and After Negative Attitude Toward Situations of Interaction with Robots

In Table 7.4, the descriptive statistics show that variations exist across the before and after negative attitude toward situations of interaction with robots. Strongly disagree group obtained the highest mean score (Mean = 4.6; S.D. = 0.548; n = 5) while feel exactly neutral group obtained the lowest (Mean = 3.43; S.D. = 0.787; n = 7). In Table 7.5, Levene's test (.571) shows that the groups are homogenous in their variances (p (Sig.) $>$ 0.05). This means that the standard deviations do not deviate greatly among the groups. Similarly, in Table 7.8, the Homogeneous Subsets of both Tukey HSD test and Scheffe test show no significant differences among before and after negative attitude toward the situation of interaction with robots, as all p $>$ 0.05.

After negative attitude toward situations of interaction with robots.

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean: Lower Bound	95% Confidence Interval for Mean: Upper Bound	Minimum	Maximum
Feel exactly neutral	7	**3.43**	.787	.297	2.70	4.16	2	4
Slightly disagree	18	4.00	.686	.162	3.66	4.34	3	5
Strongly disagree	5	**4.60**	.548	.245	3.92	5.28	4	5
Total	30	3.97	.765	.140	3.68	4.25	2	5

Table 7.4: Descriptives

After negative attitude toward situations of interaction with robots.

Levene Statistic	df1	df2	Sig.
.573	2	27	**.571**

Table 7.5: Test of Homogeneity of Variances

After negative attitude toward situations of interaction with robots.

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	4.052	2	2.026	4.236	**.025**
Within Groups	12.914	27	.478		
Total	16.967	29			

Table 7.6: ANOVA

Dependent Variable: After negative attitude toward situations of interaction with robots.

	(I) Before negative attitude toward situations of interaction with robots.	(J) Before negative attitude toward situations of interaction with robots.	Mean Difference (I−J)	Std. Error	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Tukey HSD	Feel exactly neutral	Slightly disagree	−.571	.308	.171	−1.34	.19
		Strongly disagree	−1.171*	.405	**.020**	−2.18	−.17
	Slightly disagree	Feel exactly neutral	.571	.308	.171	−.19	1.34
		Strongly disagree	−.600	.350	.218	−1.47	.27
	Strongly disagree	Feel exactly neutral	1.171*	.405	**.020**	.17	2.18
		Slightly disagree	.600	.350	.218	−.27	1.47
Scheffe	Feel exactly neutral	Slightly disagree	−.571	.308	.198	−1.37	.23
		Strongly disagree	−1.171*	.405	**.026**	−2.22	−.12
	Slightly disagree	Feel exactly neutral	.571	.308	.198	−.23	1.37
		Strongly disagree	−.600	.350	.247	−1.51	.31
	Strongly disagree	Feel exactly neutral	1.171*	.405	**.026**	.12	2.22
		Slightly disagree	.600	.350	.247	−.31	1.51

*. The mean difference is significant at the 0.05 level.

Table 7.7: Multiple Comparisons

After negative attitude toward situations of interaction with robots.

	Before negative attitude toward situations of interaction with robots.	N	Subset for alpha = 0.05	
			1	2
Tukey HSD[a,b]	Feel exactly neutral	7	3.43	
	Slightly disagree	18	4.00	4.00
	Strongly disagree	5		4.60
	Sig.		**.262**	.230
Scheffe[a,b]	Feel exactly neutral	7	3.43	
	Slightly disagree	18	4.00	4.00
	Strongly disagree	5		4.60
	Sig.		**.293**	.260

Means for groups in homogeneous subsets are displayed.

a. Uses Harmonic Mean Sample Size = 7.530.

b. The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed.

Table 7.8: Homogeneous Subsets

Table 7.6 shows the ANOVA output. Looking at the output, we can say that there are significant differences between before and after negative attitude toward situations of interaction with robots ($F = 4.236$; $df = 2$; $p < 0.05$). From Table 7.7, based on the Tukey HSD test and Scheffe test, there is a significant difference between before and after negative attitude toward situations of interaction with robots as feel exactly neutral and strongly disagree groups ($p < 0.05$).

Based on Table 7.6 and Table 7.7, we concluded that *the null hypothesis h_0 is rejected*, and hence the before and after negative attitude toward situations of interaction with robots differ significantly. In other words, the participants are having significant positive attitude change towards situations of interaction with robots after talking to the robot.

7.12.3 One-Way ANOVA Analysis: Before and After Negative Attitude Toward the Social Influence of Robots

In Table 7.9, the descriptive statistics show that variations exist across the before and after negative attitude toward the social influence of robots. Slightly disagree group obtained the highest mean score (Mean = 3.7; S.D. = 0.483; n = 10) while Slightly agree group obtained the lowest (Mean = 2.38; S.D. = 0.518; n = 8). In Table 7.10, Levene's test (.376) shows that the groups are homogenous in their variances (p (Sig.) $>$ 0.05). This means that the standard deviations do not deviate greatly among the groups. Similarly, in Table 7.13, the Homogeneous Subsets of both Tukey HSD test and Scheffe test show no significant differences among before and after negative attitude toward the social influence of robots, as all p $>$ 0.05.

After negative attitude toward social influence of robots.

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean Lower Bound	95% Confidence Interval for Mean Upper Bound	Minimum	Maximum
Slightly agree	8	**2.38**	.518	.183	1.94	2.81	2	3
Feel exactly neutral	12	2.92	.793	.229	2.41	3.42	2	4
Slightly disagree	10	**3.70**	.483	.153	3.35	4.05	3	4
Total	30	3.03	.809	.148	2.73	3.34	2	4

Table 7.9: Descriptives

After negative attitude toward social influence of robots.

Levene Statistic	df1	df2	Sig.
1.016	2	27	**.376**

Table 7.10: Test of Homogeneity of Variances

After negative attitude toward social influence of robots.

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	8.075	2	4.038	10.009	**.001**
Within Groups	10.892	27	.403		
Total	18.967	29			

Table 7.11: ANOVA

Dependent Variable: After negative attitude toward social influence of robots.

	(I) Before negative attitude toward social influence of robots.	(J) Before negative attitude toward social influence of robots.	Mean Difference (I–J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	Upper Bound
Tukey HSD	Slightly agree	Feel exactly neutral	-.542	.290	.167	-1.26	.18
		Slightly disagree	-1.325*	.301	**.000**	-2.07	-.58
	Feel exactly neutral	Slightly agree	.542	.290	.167	-.18	1.26
		Slightly disagree	-.783*	.272	**.020**	-1.46	-.11
	Slightly disagree	Slightly agree	1.325*	.301	**.000**	.58	2.07
		Feel exactly neutral	.783*	.272	**.020**	.11	1.46
Scheffe	Slightly agree	Feel exactly neutral	-.542	.290	.194	-1.29	.21
		Slightly disagree	-1.325*	.301	**.001**	-2.11	-.54
	Feel exactly neutral	Slightly agree	.542	.290	.194	-.21	1.29
		Slightly disagree	-.783*	.272	**.027**	-1.49	-.08
	Slightly disagree	Slightly agree	1.325*	.301	**.001**	.54	2.11
		Feel exactly neutral	.783*	.272	**.027**	.08	1.49

*. The mean difference is significant at the 0.05 level.

Table 7.12: Multiple Comparisons

After negative attitude toward social influence of robots.

	Before negative attitude toward social influence of robots.	N	Subset for alpha = 0.05 1	2
Tukey HSD[a,b]	Slightly agree	8	2.38	
	Feel exactly neutral	12	2.92	
	Slightly disagree	10		3.70
	Sig.		**.164**	1.000
Scheffe[a,b]	Slightly agree	8	2.38	
	Feel exactly neutral	12	2.92	
	Slightly disagree	10		3.70
	Sig.		**.190**	1.000

Means for groups in homogeneous subsets are displayed.

a. Uses Harmonic Mean Sample Size = 9.730.

b. The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed.

Table 7.13: Homogeneous Subsets

Table 7.11 shows the ANOVA output. Looking at the output, we can say that there are significant differences between before and after negative attitude toward the social influence of robots ($F = 10.009$; $df = 2$; $p < 0.05$). From Table 7.12, based on the Tukey HSD test and Scheffe test, there is a significant difference between before and after negative attitude toward the social influence of robots in slightly disagree group ($p < 0.05$).

Based on Table 7.11 and Table 7.12, we concluded that *the null hypothesis h_1 is rejected*, and hence the before and after negative attitude toward the social influence of robots differ significantly. In other words, the participants can have significant positive attitude change towards the social influence of robots after talking to the robot.

7.12.4 One-Way ANOVA Analysis: Before and After Negative Attitude Toward Emotions in Interaction with Robots

In Table 7.14, the descriptive statistics show that variations exist across the before and after negative attitude toward emotions in interaction with robots. Slightly disagree group obtained the highest mean score (Mean = 3.94; S.D. = 0.443; n = 16) while slightly agree group obtained the lowest (Mean = 3.00; S.D. = 1.414; n = 2). In Table 7.17, the Homogeneous Subsets of both Tukey HSD test and Scheffe test show no significant differences among before and after negative attitude toward emotions in interaction with robots, as all $p > 0.05$.

After negative attitude toward emotions in interaction with robots

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
Slightly agree	2	**3.00**	1.414	1.000	-9.71	15.71	2	4
Feel exactly neutral	12	3.25	.866	.250	2.70	3.80	2	4
Slightly disagree	16	**3.94**	.443	.111	3.70	4.17	3	5
Total	30	3.60	.770	.141	3.31	3.89	2	5

Table 7.14: Descriptives

After negative attitude toward emotions in interaction with robots

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	4.013	2	2.006	4.108	**.028**
Within Groups	13.188	27	.488		
Total	17.200	29			

Table 7.15: ANOVA

	(I) Before negative attitude toward emotions in interaction with robots	(J) Before negative attitude toward emotions in interaction with robots	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Tukey HSD	Slightly agree	Feel exactly neutral	-.250	.534	.887	-1.57	1.07
		Slightly disagree	-.938	.524	.192	-2.24	.36
	Feel exactly neutral	Slightly agree	.250	.534	.887	-1.07	1.57
		Slightly disagree	-.688*	.267	**.041**	-1.35	-.03
	Slightly disagree	Slightly agree	.938	.524	.192	-.36	2.24
		Feel exactly neutral	.688*	.267	**.041**	.03	1.35
Scheffe	Slightly agree	Feel exactly neutral	-.250	.534	.897	-1.63	1.13
		Slightly disagree	-.938	.524	.221	-2.30	.42
	Feel exactly neutral	Slightly agree	.250	.534	.897	-1.13	1.63
		Slightly disagree	-.688	.267	.051	-1.38	.00
	Slightly disagree	Slightly agree	.938	.524	.221	-.42	2.30
		Feel exactly neutral	.688	.267	.051	.00	1.38

*. The mean difference is significant at the 0.05 level.

Table 7.16: Multiple Comparisons

After negative attitude toward emotions in interaction with robots

	Before negative attitude toward emotions in interaction with robots	N	Subset for alpha = 0.05 1
Tukey HSD[a,b]	Slightly agree	2	3.00
	Feel exactly neutral	12	3.25
	Slightly disagree	16	3.94
	Sig.		**.121**
Scheffe[a,b]	Slightly agree	2	3.00
	Feel exactly neutral	12	3.25
	Slightly disagree	16	3.94
	Sig.		**.143**

Means for groups in homogeneous subsets are displayed.

a. Uses Harmonic Mean Sample Size = 4.645.

b. The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed.

Table 7.17: Homogeneous Subsets

Table 7.15 shows the ANOVA output. Looking at the output, we can say that there are significant differences between before and after negative attitude toward emotions in interaction with robots (F = 4.108; df = 2; $p < 0.05$). From Table 7.16, based on the Tukey HSD test and Scheffe test, there is a significant difference between before and after negative attitude toward emotions in interaction with robots in feel exactly neutral and slightly disagree group ($p < 0.05$).

Based on Table 7.15 and Table 7.16, we concluded that *the null hypothesis h_2 is rejected*, and hence the before and after negative attitude toward emotions in interaction with robots differ significantly. In other words, the participants can have significant positive attitude change towards the emotions in interaction with robots after talking to the robot.

7.13 Contributions

The following items are the contributions of this chapter:

1. The experimental result supported that our proposed spiking reflective processing model can generate new intuitions for the robot partner daily conversations with its users. The generated new intuitions are relatively related to the environment context information as revealed by our test subjects. Furthermore, these new intuitions generation behaviours are similar to the behaviours discussed in affordance theory [62] (Chapter 2 subsection 2.5.2).

2. Our proposed spiking reflective processing gives a more detailed explanation of the affordance theory [62] (Chapter 2 subsection 2.5.2) and the mechanism of the new intuition creation process that inspired from Spiking Neural Network [61] model.

3. Our proposed spiking reflective processing (Section 6.3) consist of a Spiking Neural Network (SNN) [61] model, stress-inspired model and the robot partner's working memory model that explains the human's new intuition creation behaviour.

4. The experimental results indicated significant positive feedback from the test subjects in term of social, emotional and perception improvements after the human-robot interaction experiments.

7.14 Chapter Summary

A novel spiking reflective processing model is proposed and implemented for the robot partner new intuition creation behaviour.

The proposed Spiking Reflective Processing model focuses on the regulation of working memory using biological stress models. This model can be applied to many social scenarios, such as schools, workplaces, retail, hotels, restaurants and so on. And the "robot partners" concept is taken in this wide sense. In my thesis I chose the elderly as this is one of the most challenging demographics.

Therefore, this thesis work is not about producing an eldercare robot, but it is about producing a biologically inspired working memory to produce Human Robot Interaction (HRI) with better EQ and IQ.

In this research, we focus on the human-robot conversation with its users in the perspective of robot partner's new intuition creation behaviour. Furthermore, the human's stress response system (subsection 2.3.1), multi-component working memory model [9] and Spiking Neural Network [61] inspired our proposed spiking reflective processing model design. Our proposed model postulates that the similarity between environment context information and reference memory triggered the Spiking Neural Network structure activation for new intuition creation behaviour. Thus, understanding the human spiking reflective processing model mechanism enables the development of robot partner's its new intuition creation behaviour during an ambiguous situation.

The experimental results from the test subjects survey after the human-robot interaction empirically supported our proposed model that will socially and emotionally help the elderly people.

Chapter 8

Conclusion

8.1 Main Contributions

8.1.1 Novel Stress Model Integrated into Markov Decision Process Method for Solving Dynamic Environment Problem

In Chapter 3, our novel biologically inspired stress-based model had integrated the neural network-based perception-action learning and fuzzy logic models to determine the appropriate action group to be selected. Hence, the agent can learn complex action was shown to reduce the full steps required for the simulated agent to reach its designated goal with dynamic obstacles in its environment. We integrated our working memory model to that of the agent with stress inspired regulations on its working memory retrieval scope. The agent's action selection tasks according to its stress conditions in different experiment execution environments. For example, during middle-stress conditions the agent will be able to consider more actions, but during low and high-stress conditions the agent will not consider a large number of actions. The reason is that of different working memory retrieval performance behaviour according to the stress levels [106]. Hence, our model's action selection behaviours enable the agent to select the learned best actions to mitigate its dynamic obstacles effectively in our benchmark comparison experiments.

8.1.2 Two Novel Genetic Operators for Improving Optimisation Performance of Fuzzy Logic System

In Chapter 4, we proposed two novel genetic operators to improve the overall optimisation accuracy by reducing the *inbreeding depression* [79] phenomenon in the chromosome population. For example, similar genes in the population are not required to be mutated or to be gene transferred thus improving the overall evolutionary computation optimisation performance.

The proposed genetic operators can outperform the benchmark approaches in commonly used fuzzy logic's rules in optimisation problem datasets. The experimental results indicated that our proposed model did not impose significant additional training time to improve the optimisation accuracy.

8.1.3 Novel Robot Partner's Dynamic Working Memory Optimisation Model with Guessing Game System

In Chapter 5, we integrated the two novel evolutionary computation genetic operators into the robot partner's working memory optimisation. The purpose of the working memory optimisation is to reduce the image concept detection noise (incorrectly detected concepts) in its working memory. On top of that, the chromosome population (working memory) is dynamically updated to simulate the volatile behaviour of the human working memory. The proposed working memory evolutionary computation optimisation model is to simulate the proactive control of dual mechanisms of cognitive control (definition 1.8.1) [26].

Furthermore, the robot partner's working memory optimisation scope changes according to the different stress conditions in the game for effective optimisation behaviour [106]. Our novel stress-based model can outperform the benchmark approaches regarding working memory optimisation accuracy. Hence, the robot partner can effectively guess the object's concept by reducing the image detection noise with the clues given in the game of 20 questions.

8.1.4 Novel Spiking Reflective Processing Model Supported by Empirical Evidences

In Chapter 6, we proposed the spiking reflective processing model with synthetic modelling [135] methodology (definition 2.1.1) consideration. In the synthetic modelling point of view, we considered the biological, psychological, philosophical and computational literature point of view before proposing our model. Furthermore, the result findings supported our proposed model by the empirical evidence from participants in a university population.

8.1.5 Novel Spiking Neural Network Intuition Creation Model Based on the Robot Partner's Daily Conversation System

In Chapter 7, we implemented the spiking reflective processing model in Chapter 6 for the robot partner embodied cognitive intelligence. We emphasised in human-robot conversation with its users in the perspective of robot partner's new intuition creation behaviour. Our proposed model postulates that the similarity between environment context information and reference memory triggered the Spiking Neural Network structure activation and thus triggered the robot partner's intuition creation. The experimental results from the participants survey after the human-robot interaction empirically supported our proposed model that will socially and emotionally help the users.

8.2 Answering Research Questions

8.2.1 Research Question 1: RQ1

What are the current problems in robot partner support for elderly people?

The research question RQ1 had been answered in Chapter 1 Section 1.2. We listed the problems in the ageing society and the potential of robot partner's contributions in different scenarios.

8.2.2 Research Question 2: RQ2

Cognitive intelligence is said to be an important factor of human intelligence. What is it exactly? And what are the state-of-the-art cognitive models in current robot partner?

The research question RQ2 had been answered in Chapter 6. To understand what is cognitive intelligence, we verify our proposed spiking reflective processing model with established psychology test in Chapter 6 Section 6.7. Our experimental results in Section 6.8 consist of empirical evidence to support our proposed model. These findings are crucial in the cognitive intelligence research field; the reason is our proposed model focused the important conditions for the robot partner to initiate its new intuition. The potential impact of our discovered model is substantial because we considered our model design with actual human participants new intuition generation behaviours and not any arbitrary engineering approach.

8.2.3 Research Question 3: RQ3

Can we improve the state of the art cognitive intelligence for robot partners by applying biological principles?

For research question RQ3, we can conclude that the existing state-of-the-art in cognitive intelligence robot partners has many shortcomings, and critically, we have not found any existing models [102, 113] which accurately model the biological cognitive processes, specifically the new intuition creation process during ambiguous situations that model the robot partner's working memory and stress response system. To answer research question RQ3, this research develops the spiking reflective processing model (Chapter 7 Section 7.8), which is centred on the idea that stress regulates working memory, and it is a key factor in human-like cognitive intelligence. Furthermore, in Chapter 7 Section 7.12, we discovered in our survey that the participants had overall positive feedback towards human-robot interaction with the robot partner that integrated with the proposed model.

8.3 Research Publications

The publications arising from this Ph.D. research are listed as follows:

1. Reinforcement Learning in Non-Stationary Environments: An Intrinsically Motivated Stress Based Memory Retrieval Performance (SBMRP) Model [171]

2. Dynamic Programming in the Perspective of Guided Gene Transfer in Bacterial Memetic Algorithm [168]

3. Average Edit Distance Bacterial Mutation Algorithm for Effective Optimisation [167]

4. Stress-Inspired Dynamic Optimisation on Working Memory for Cognitive Robot Social Support Systems [170]

5. Reflective Processing Model in the Perspectives of Working Memory and Stress for Human-Robot Communication Application (We will publish Chapter 6 in Minds and Machines Journal)

6. Stress-inspired Working Memory Reflective Processing for Robot Partners (We will publish Chapter 7 in International Journal of Social Robotics)

7. Fuzzy Spiking Neural Network for Abnormality Detection in Cognitive Robot Life Supporting System [166]

8.4 Summary of Findings

Below are the main findings from this Ph.D. research:

1. The agent's embodied cognitive intelligence is related with working memory and stress response system with empirical evidence to support these findings in Chapter 6.

2. The development of robot partner's embodied cognitive intelligence is possible with our proposed spiking reflective processing model (Chapter 7) that focus on Spiking Neural Network, working memory and stress response system with synthetic modelling methodology [135] (definition 2.1.1) considerations.

3. The proposed spiking reflective processing model (Chapter 7) is the *dual mechanisms of cognitive control* [26] involving the working memory dynamic optimisation (proactive control) and new intuition creation and their inter-transitions behaviours. We argue that the inter-transitions behaviours of these two cognitive control mechanisms as the *essence of embodied cognitive intelligence.* The reason is the inter-transitions behaviours of these two cognitive control mechanisms fully attribute the definition of embodied cognitive intelligence (definition 1.6.7). *Embodied cognitive intelligence* is the learning ability that involves the agent's brain and its body systems (i.e. stress response system) for an agent to *guess* or *construct* the meanings of the perceived environmental information and generate its new intuition efficiently to react for ensuring its survival in the dynamic environment.

4. The proactive control of *dual mechanisms of cognitive control* [26] by working memory dynamic optimisation illustrated the agent's intention that influences the situation scenario [170] (Chapter 4).

5. The reactive control of *dual mechanisms of cognitive control* [26] is a new intuition creation or reflective processing [151] mechanism for the working memory to trigger a new intuition (Chapter 7).

6. In Chapter 7, the robot partner's new intuition generation required the similarity between short-term memory content and long-term memory content. Hence,

these short-term memory content and long-term memory content will enable the similarity's comparison algorithm in our proposed spiking reflective processing model (section 7.8) to generate the fire condition in the Spiking Neural Network (SNN) for new intuition creation behaviour.

7. The robot partner sometimes creates cognitive biases or systematic errors [11, 83, 179] during its heuristic behaviour to guess its environment's meanings with only partially available information about the environment. However, the cognitive biases do not impact the overall positive survey feedback from the participants in the human-robot communication experiment (Chapter 7).

8. A general knowledge inference system [98] acts as the robot partner's reference memory (long-term memory content) for dynamic local optimisation in its working memory (subsection 5.7.5). The long-term memory content is linked ontologically with content in the agent's working memory. Then, the proactive control [26] processing will load the long-term memory content into the working memory. Besides, more inferences are needed during middle-stress conditions where the robot partner needs more *considerations* for reflective processing. The inference system involves heavy processing of its retrieval process. Therefore, it is natural that the robot partner only considers this heavy processing in certain scenarios during its middle-stress conditions, the reason is robot partner can freely create its new intuition with less penalisation from the environment during middle-stress conditions.

8.5 Advantages and Limitations of the Proposed Spiking Reflective Processing Model

In this section, we will discuss the identified limitations and benefits of the proposed spiking reflective processing model in this research:

8.5.1 Advantages of the Proposed Spiking Reflective Processing Model

8.5.1.1 Timing of New Intuition Creation Behaviour is Known

It is important to understand the timing (or when) robot partner to initiate the new intuition creation behaviour (reactive control) or optimise (proactive control) with its working memory [26]; this is to simulate robot partner's survival [135] behaviour.

For example, if robot partner is in high-stress conditions then the robot partner will not execute new intuition creation behaviour in such environment to reduce risk in a critical situation. Hence, the robot partner's survival (definition 1.5.1) heavily depends on its fast and contextualised actions according to the environment situations to reduce errors.

8.5.1.2 Biology Inspired Embodied Cognitive Intelligence Approach

The biological models such as stress response system, working memory and Spiking Neural Network (SNN) inspired the proposed spiking reflective processing model. We considered the synthetic modelling methodology [135] (definition 1.8.1) for our model design. Hence, our proposed model is a natural representation of agent's embodied cognitive intelligence to enhance human-robot communication during uncertain situations. On the contrary, the non-biological inspired engineering approach is not ideal to model for human-robot interactions, the reason is there is no concrete evidence to support the recreation of embodied cognitive intelligence with any arbitrary engineering method.

8.5.1.3 Coherent to Many Cognitive Intelligence Theories that Emphasise Working Memory

In our proposed spiking reflective processing model is coherent with the state-of-the-art understanding of cognitive intelligence. We focused on fundamental understanding of human's models such as working memory [4, 5, 34, 62], heuristic techniques [134, 149, 176], cognitive load [165], dual mechanisms of cognitive control [26] and natural data observation [62, 77] of the environment.

8.5.1.4 Efficient New Intuition Creation Process in High Dimensional Natural Data Environment

The proposed spiking reflective processing model can quickly create new intuition in a high dimensional natural data environment. The reason is that the contraction and expansion of the working memory retrieval performance in different robot partner's stress arousal levels can reduce the total dimension of data consideration for new intuition creation.

8.5.2 Limitations of the Proposed Spiking Reflective Processing Model

8.5.2.1 Cognitive Intelligence Impairs During High-Stress Conditions

During high-stress arousal, the robot partner's cognitive intelligence is impaired in leading to less new intuition creation. The reason is that the robot partner's stress response system will not enforce new intuition creation behaviour to solve the environment's problem. However, this may not an issue for a short period as the robot partner will not try any new intuition in a high-risk environment (high-stress environment), but if the stress from the environment continues, the robot partner may not be able to resolve the situation with new intuition creation.

8.5.2.2 Cognitive Intelligence Impaired during Low-Stress Conditions

In situations of low-stress arousal, the robot partner's cognitive intelligence will be impaired with less new cognitive product (new intuition) creation. The reason is that the robot partner will not try new intuitions to solve an issue in the environment. However, this is not a problem in the short term because there is no risk in the environment. In the long run, the robot partner may not be pro-active to suggest new intuitions to improve its situation if there is little or no stress at all.

8.5.2.3 High Computation Cost of Inference System and Image Concept Detection Framework

The computational cost of the inference system module [98] and image concept detection module [80, 81, 147] are relatively high in current commercial computing hardware technology. Therefore, the robot partner computing hardware alone cannot perform the embodied cognitive intelligence computation tasks. Instead to process the inputs in robot partner's limited computing power hardware, the server side resources will process the embodied cognitive intelligence task in this research's proposed approaches in Chapter 5 and Chapter 7.

8.6 Discussion

The proposed robot partner's spiking reflective processing model (section 7.8) is a biologically inspired approach. In the previous section 8.5, we discussed the advantages and limitations of our proposed model. The main advantage of integrating biological stress response system into embodied cognitive intelligence is the ability to create relevant new intuitions within a short time in a high-dimensional environment context information environment.

The focus of the robot partner's embodied cognitive intelligence is on the new intuition creation but not on the optimum solution; new intuition creation can identify a large permutation of a solution in a short time. It is a crucial understanding because to operate in a high-dimensional natural data environment, for any dynamic setting environment, the optimum solution is not recommended because it only performs in a static environment. For a static environment example such as a chess game, the total possible number of movements are well defined. As a result, a standard optimisation approach can easily compute an optimum solution in a static environment such as a chess game. In contrast, for a dynamic environment example, if a person goes to market by driving a car, the total possible actions the driver can take are vast where there are many unforeseen circumstances such as road accidents, pedestrian movements, road conditions and weather conditions. Thus, the total number of possible movements of permutation combinations in a natural data environment is too large for any standard optimisation approach. In other words, our proposed spiking reflective processing model is reactive-based new intuition creation behaviour for operating in a high-dimensional natural data environment. Reactive-based means the new intuition generation is on-demand, the environment's stimuli is responsible for triggering the robot partner's new intuition creation.

However, the proposed biological stress-inspired spiking reflective processing model also inherits many disadvantages from the biological system as well. As discussed in the previous sections, during low and high-stress conditions the robot partner will have cognitive intelligence impairment to create new intuition to resolve the stress from the environment. Nevertheless, these limitations may not be an issue when the robot partner is operating in a high-dimensional environment. Creating new intuition in such environment requires embracing the risk of failure. The possibility of such failures created by the new intention is high for low-stress and high-stress conditions as discussed earlier.

Furthermore, the proposed model in this research only focuses on stress emotion instead of other emotion types such as happiness, fear, sadness, anger, disgust and surprise as discussed by Paul Ekman [46]. The reason is stress emotion is the only emotion that has empirical evidence to support the working memory retrieval performance's Gaussian relationship with the agent's stress arousal level [106]. Consequently, additional research is required to verify the relationships between other emotion types [46] and the agent's working memory retrieval performance. Investigation of other emotion types about the working memory retrieval performance for the robot partner will be our future research directions.

Also, this research supports the view of Mayer and Salovey [114] that positive (happy) and negative (sad) emotions are empirically related to cognition behaviours. As they stated, "We have recently found that both happy and sad moods are followed by a *shift in attention inward*: such a shift would seem to promote cognitive and behavioural activities". Hence, the proposed model in this research also suggests that the robot partner's cognitive intelligence model is the *functional integration of the positive and negative emotions*. Furthermore, the mentioned *shift in attention inward* is simulated as the new intuition creation mechanism model based on the spiking neural network in this research in Chapter 7. The agent's new intuition creation mechanism generated the positive emotion in the assumption of this study. For example, a person is happy when he finds a solution to solve a difficult problem; the feeling of success to solve a problem (cognition) is the happy emotion. Thus, this phenomenon is named as the *functional integration of positive and negative emotions* in this research.

8.7 Future Research Directions

This Ph.D. work has open up several directions where future research may take:

8.7.1 Genetic Optimisation Future Work

In future work, different gene comparison methods will be investigated to resolve optimisation problems. Then, larger datasets will be tested for larger data optimisation analysis. The DPGT and AEDBM optimisation methods will be investigated to solve more general fuzzy logic rules optimisation problems.

8.7.2 Dynamic Time Warping Extension

For future extension of the proposed DBMA approach, it could be used to investigate the time series property of dynamic time warping capability and compare with a non-linear gene similarity model.

8.7.3 Neuromorphic Chip Implementation

The neuromorphic chip implementation for the spiking neurone network model is needed to reduce the total processing time for better human-robot communication experience. It is essential to have real-time human-robot communication to improve the human-robot engagement.

8.7.4 Electroencephalogram (EEG) Test

For future extension of the proposed Chapter 6 approach of modelling human's reflective processing behaviours, Electroencephalogram (EEG) could be used to enhance the measurement of test subject's stress level with better precision and accuracy.

8.7.5 Robot Partner Acceptance Test Experiment at Nursing Care Home

For future work, the proposed spiking reflective processing model (Chapter 7) could be applied in term of the elderly people's acceptance as human-robot communication efficacy test. It is to ensure the robot partner with proposed model can operate seamlessly with the elderly at a nursing care home.

8.7.6 Improve the Working Memory Content Binding Method

The proposed spiking reflective processing model (Chapter 7) could be improved by measuring uncertainty energy in the agent's working memory contents for binding.

8.8 Thesis Summary

The proposed robot partner biologically inspired spiking reflective processing model (section 7.8) is an efficient new intuition creation mechanism to operate in any unpredictable natural data environment. Although this is an initial work for such a robot partner embodied cognitive intelligence system, many promising applications that require new intuition creation ability can be derived, for example, creative thinking robot partner applications in any environment context information conditions.

To serve the ageing population, biologically competent embodied cognitive intelligence such as spiking reflective processing model is crucial for any human-robot communication application. The reason is the notion of free will (decision-making ability) in embodied cognitive intelligence is required for the robot partner to operate effectively and efficiently in an ambiguous high-dimensional natural data environment.

In short, robot partner needs to survive [135] (definition 1.5.1) in such uncertain environment context information conditions with a swift response.

However, such embodied cognitive intelligence artificial agent raises many interesting questions such as: Is it possible that the human is willing to give the privilege of one's free will to an artificial agent? What if such new intuition creation causes non-calculated risk or cognitive biases or systematic errors [11, 83, 179]? Will humans be able to accept such errors created by the robot partner's heuristic techniques? For human-to-human interaction scenarios, these questions can easily be answered, but in robot-to-human interaction scenarios, people will still find it hard to accept such errors generated by the robot partner. Nevertheless, these questions are beyond the scope of this research.

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Acronyms and Glossary

6DIMS Six-Dimension Generic Function. xvii, xxiii, 89, 91–95

ACTH adrenocorticotropic hormone. 23

AEDBM Average Edit Distance Bacterial Mutation. xvii, xviii, xxii, xxiii, 77, 79, 86, 87, 89, 91, 93–98, 105–110, 114, 152, 154, 155, 191

agent *Agent* is a living organism or artificial life that exhibits intelligent behaviours that agent can adapt and survive in any given uncertain environment. xxiii, 5–7, 9–11, 13–15, 17, 20, 21, 25–27, 33, 34, 38, 39, 44, 47, 50–64, 66, 68–72, 74, 77, 78, 80, 81, 91, 100, 103, 104, 107, 116–121, 141, 142, 144, 148, 182, 186, 190, 191, 193

AGRI Agricultural Data. xvii, xxiii, 90–95

AICO Advanced Intelligence Cognitive Optimisation. xviii, 99, 100, 111, 112, 114, 258

Alzheimer *Alzheimer* is a chronic neurodegenerative disease that commonly begins slowly and becomes worse over time. 4, 15, 102, 142, 174

amygdala *Amygdala* is an almond-shaped mass located in the centre of the brain. It is also the brain's memory organ that stores the emotion memories such as flashbulb and traumatic memories. 23–25

analytic system *Analytic system* would be slow and heavily demanding of human's computational resources and working memory. 15, 116

ANN Artificial Neural Network. 63, 65, 69, 143

ASFQ Adaptive State Focus Q-learning. xvii, 58, 59, 69, 71, 72

BEA Bacterial Evolutionary Algorithm. 81

BMA Bacterial Memetic Algorithm. xvii, xviii, xxii, 77–80, 83, 87, 93–98, 105, 152, 154

CAM Concept-Action Mapping. xviii, xxiii, 91–97

central executive control *Central executive control* is the agent's working memory system component that performs switch attention, focus attention, divide attention and link to long-term memory. It is a purely attentions control system for the agent. 118, 119

CI Cognitive Intelligence. 7, 8

COG centre of gravity. 81

cognitive biases *Cognitive biases* refer to the suggestion errors or systematic errors of an action that could be caused by insufficient or corrupted given information to make a decision for an action. 36, 37, 187, 193

cognitive intelligence *Cognitive intelligence* is the learning ability for an agent to *guess* or *construct* the meanings of the perceived environmental information and generate its new intuition efficiently to react for ensuring its survival. 7–13, 18, 19, 21–23, 25, 26, 28–31, 38–46, 48, 51, 55, 75, 81, 99, 101, 115, 141, 146, 147, 149, 172, 184, 185, 188–191

cognitive load *Cognitive load* refers to mental efforts assigned to working memory information processing. 36, 38, 45, 75–77, 100, 101, 114, 149, 188

cognitive product *Cognitive product* is a new intention or new intuition constructed with the agent's working memory. 32, 49, 61, 66, 120, 189

CRH corticotropin-releasing hormone. 22, 23

CRT Cognitive Reflection Test. 123

DBMA Dynamic Bacterial Memetic Algorithm. xviii, xxii, xxiii, 105–108, 110–114, 152, 191

dementia *Dementia* is a mental process chronic disorder caused by brain disease or injury and marked by personality changes, memory disorders and impaired reasoning. 4, 15, 99, 102, 142, 174

DP dynamic programming. 77, 78, 82, 83, 108

DPGT Dynamic Programming Gene Transfer. xvii, xxii, 77–79, 81–83, 85, 86, 91, 98, 105–107, 110, 111, 114, 152, 154, 155, 191

dual mechanisms of cognitive control *Dual mechanisms of cognitive control* theory suggest that cognitive control is consists of two distinct control mechanisms that are proactive control and reactive control. vi, 13, 14, 17, 20, 31, 38, 39, 46, 48, 100, 142, 146, 183, 186, 188

dual-process theory *Dual-process theory* is the dual systems explanation of human's cognitive response model with System 1 and System 2 processes. 10, 115–117, 120, 121, 140, 141, 146

EC evolutionary computation. 14, 76–79, 81, 100, 101, 105

EEG Electroencephalogram. 192

EI Emotional Intelligence. 7

embodied cognitive intelligence *Embodied cognitive intelligence* is the learning ability that involves the agent's brain and its body systems (i.e. stress response system) for an agent to *guess* or *construct* the meanings of the perceived environmental information and generate its new intuition efficiently to react for ensuring its survival. v, 7, 10, 11, 14–17, 19–22, 24, 26–31, 34, 35, 38, 42, 46–50, 55, 99–101, 103, 104, 122, 140, 142, 147, 184, 186, 188–190, 192, 193

environment context information *Environment context information* are the inputs information that an agent can sense from the natural data environment. For example, sound, image, taste, touch feeling and smell. v, vi, 15, 36, 42, 101, 116, 117, 121, 142, 144, 146, 149, 172, 179, 180, 184, 190, 192, 193

episodic buffer *Episodic buffer* is believed to be able of storing information into the working memory in the form of multi-dimensional code. The episodic buffer also provides a short-term interface between the slave systems of working memory system that are the phonological loop, visuospatial sketchpad) and the long-term memory. It is presumed to be controlled by the central executive control, which the central executive control is known for binding information from some different sources into coherent episodes. 118, 119, 121, 140

EQ Emotional Quotient. 7, 21, 180

FFQ Friend-or-Foe Q. xvii, 58, 69, 71, 72

free will *Free will* is refers to the ability to act at one's own discretion. 13, 48, 76, 192, 193

GA Genetic Algorithm. 143, 144

global workspace theory *Global workspace theory* explains the agent's cognitive intelligence with a theater metaphor. 42, 44, 45, 110

glucocorticoid *Glucocorticoid* is a type of peptide stress hormone produced by an organism during its anxiety condition. xvi, 23–25, 34, 35, 61, 105, 106, 149

heuristic *Heuristic* refers to trail-and-error behaviours that are able to suggest a intermediate solution to a given complex problem (mental shortcuts) that also reduces the cognitive load of a person. 26, 31, 32, 35, 36, 41, 44, 76, 144, 146, 149, 150, 152, 187, 188, 193

heuristic system *Heuristic system* or *intuitive system* that will tend to mitigate a problem by depending on prior knowledge and beliefs. 116

hippocampus *Hippocampus* is the curved elongated ridge that is a part of the brain that connected to Amygdala, it is also known to be involved in forming, storing, and processing reference memory. 23, 24

HOCP Human Operation in the Chemical Plant. xvii, xviii, xxiii, 90–96

HPA hypothalamic-pituitary-adrenal. xvi, 22, 23, 54, 103, 149

HRI Human Robot Interaction. 180

human-robot *Human-robot interaction* refers to human-to-robot communication session. vi, xix, xxiii, 4, 7, 14–16, 20, 27, 28, 30, 32, 36, 42, 74–77, 87, 99–101, 112, 113, 140–144, 146, 147, 149–151, 154, 157–160, 170–174, 180, 181, 184, 185, 187, 188, 192

intention *Intention* is the goal or objective of the agent. 7, 9, 12, 13, 32, 36, 39–41, 49, 51, 75, 76, 87, 100, 105, 152, 186

inverted-U *Inverted-U* shape means a 2-axis graph relationship that is similar to a Gaussian shape or bell shape. 20, 29, 30, 35, 48, 49, 52, 59, 61, 74, 121, 129, 130, 147, 148

iPhonoid *iPhonoid* is a low cost smart phone robot that is built with 3D printable materials, low cost servos and iPhone touch screen. 99, 100, 102, 111, 112, 258

IQ Intelligence Quotient. 8, 21, 180

LM Levenberg-Marquardt. 78–80

long-term memory content *Long-term memory content* is the reference memory that is triggered and loads into the working memory. For example, a visual input of umbrella may trigger reference memory of rain loads into the working memory that based on the semantic relationship of the concepts. 13, 24, 32, 120, 121, 123, 124, 128, 130, 146, 148, 154, 186, 187

MARL Multi Agent Reinforcement Learning. 68

MDP Markov Decision Process. v, 33, 48, 56, 74

memetic Computation optimisation approach that combines local and global search operators. 78, 79

MF Membership Function. 91

MSE Mean Square Error. xvii, xviii, xxiii, 85, 86, 91, 93–98

NAO *NAO* is a children size humanoid robot platform that was created by Alderbaran Robotic in France. 150, 154, 157

NARS Negative Attitude Toward Robots Scale. xxiii, 171–173

natural data *Natural data* refers to the high-dimensional streaming input sensing data from the surrounding environment such as sound, visual input, touch, smell and taste. 16, 40, 41, 44–46, 48, 101, 188, 190, 192

natural environment settings *Natural environment settings* are the experiment's environmental settings that emphasise the importance of real world environmental factors. 8, 9, 16

new intuition In our proposed spiking reflective processing model, the *new intuition* refers to a new idea or new intention or new cognitive product resulted from the spiking reflective processing model that fires after the spiking neural network membrane potential exceeded its threshold. The new intuition is created with the combination of long-term and short-term memory contents in the agent's working memory. The generated new intuition is also known as episodic buffer in Alan Baddeley's multi-components working memory model. v, vi, xix, 7–10, 12–15, 17, 24, 26, 32, 36, 37, 39, 40, 44, 46, 47, 51, 55, 76, 103, 104, 117, 119–121, 142, 146, 148–150, 152, 154, 156, 172, 179, 180, 184–193

optimisation To solve NP hard problem, algorithms are used that will be stopped in a finite number of steps, or repeated processes that converge to a solution or approximate solutions to the problems. vi, xviii, 7, 9, 13–15, 17, 26, 31, 33, 37, 39, 41, 44, 47, 49, 56, 74–80, 83, 86, 87, 93, 96–102, 104–108, 111–114, 150, 152, 182, 183, 185–187, 190, 191

phonological loop *Phonological loop* is part of agent's working memory system for storing speech-based information, for an example digits in the digit span test. 118

PlainQ Q-learning. xvii, 57, 71–73

prefrontal cortex *Prefrontal cortex* is the brain area located behind the forehead. It is also the area for processing the agent's working memory and down-regulation of stress response system. 15, 23, 25, 26

proactive control *Proactive control* is a strong goal-relevant focus, future-oriented, early selection, preparatory attention behaviours that actively optimises the agent working memory towards the designated intention. Proactive control is one of the cognitive control in dual mechanisms of cognitive control theory. vi, 12–14, 32, 37, 39, 41, 49, 100, 183, 186, 187

PSP Post-Synaptic Potential. 156

PSS Perceived Stress Scale. xviii, 123, 125, 128, 129, 140

raw data *Raw data* refers to the high-dimensional streaming input sensing data from the surrounding environment such as sound, visual input, touch, smell and taste. 15, 150, 159

reactive control *Reactive control* is an increased goal-irrelevant processing, item-specific control, past-oriented, late correction behaviours that passively create new intuition based on the agent's working memory. Reactive control is one of the cognitive control in dual mechanisms of cognitive control theory. 12–14, 22, 36, 37, 39, 41, 77, 142, 146, 186, 187

reference memory *Reference memory* is refers to agent's long-term memory or memory that can be consciously recalled such as knowledge and facts. 10, 23, 24, 31–33, 39, 110, 187

reflective processing *Reflective processing* is a system 2 processing behaviour in dual-process approach where the response produced is highly dependent on agent's working memory during an ambiguous situation. 15, 115–121, 140, 141, 146, 147, 150, 156, 186

Rényi-Ulam *Rényi-Ulam* is a guessing game based on popular "20 Questions" game. The player needs to guess a concept from a series of 20 questions with replies of yes and no from the other player. xviii, 15, 100, 102, 103, 105, 108, 111, 112, 114

retrieval performance *Retrieval performance* refers to the total working memory scope that can be accessible for the agent's working memory cognitive control processing. 8, 9, 11, 14, 21–23, 30, 31, 33–35, 43–45, 47, 48, 51, 54, 55, 59, 61, 64, 66, 100, 104, 105, 119, 121, 148, 149, 157, 182, 188, 190, 191

RF Reference Memory. 10

robot partner Robot partner is an intelligent robot that works, operates, survives and communicates with its human user as well as with another robot partner. The robot partner can also be considered as a human's companion robot. 1, 2, 4–7, 11, 12, 14–17, 19, 20, 25–32, 34–37, 40–44, 46–51, 75–77, 86, 87, 89, 99–108, 110–112, 114, 115, 117, 122, 140–144, 146, 147, 149–152, 154–158, 170–172, 174, 179, 180, 183–193, 258

ROS Robot Operating System. 157

RQ1 Research Question 1. 3, 184

RQ2 Research Question 2. 7, 115, 184

RQ3 Research Question 3. 20, 51, 75, 99, 141, 172, 174, 185

SARSA State Action Reward State Action. xvii, 57, 71–73

SBMRP Stress Based Memory Retrieval Performance. xvi, xvii, 54, 59–62, 66, 67, 69, 71–74

short-term memory content *Short-term memory content* is referred to context information from the environment such as audio input, visual input and tactile inputs that temporarily stored in working memory. 13, 24, 120–124, 128, 130, 146, 148, 150, 186, 187

situation *Situation* in this research refers to the stored working memories about currently perceived environmental context information and reference memory (referenced into working memory). 9, 13, 39, 41, 42, 75, 186

SNN Spiking Neural Network. v, 10, 46, 120, 121, 128, 141, 143, 144, 151, 152, 154–156, 180, 184, 186–188

spiking reflective processing *Spiking reflective processing* is a model proposed in this research for improved understanding of system 2 processing behaviour in dual-process approach where the response produced from spiking neural network fires phenomena and it is highly dependent on agent's working memory during an ambiguous situation. vi, xix, 6, 9, 14, 15, 17, 42, 46, 115, 119–122, 128, 139–143, 146–152, 154, 155, 172, 174, 179, 180, 183–190, 192

SRPDBMA Spiking Reflective Processing Dynamic Bacterial Memetic Algorithm. xxii, 151, 152, 154–157

STAI State-Trait Anxiety Inventory. xviii, 122–124, 126, 128–130, 138–140, 170, 171

steroidogenesis *Steroidogenesis* is the steroid hormones generation process with glands such as testes, adrenal cortex and ovaries. 23

stochastic *Stochastic* refers to a random search process in computational optimisation. 79, 93, 106, 152

stress arousal *Stress arousal* refers to an organism's stress hormone status during its anxiety condition. 27, 29, 31, 47, 51, 52, 54, 55, 59, 61, 64, 66, 74, 120, 121, 123, 147–149, 151, 156, 157, 188–190

stress response system *Stress response system* is referred to the hypothalamic-pituitary-adrenal (HPA) axis of stress hormone regulation system in the body. v, 10, 11, 14, 17, 21–26, 31–35, 44, 47, 49, 50, 54, 56, 103, 119, 141, 147, 149, 151, 180, 185, 186, 188–190

System 1 *System 1* is the process of judgments that are high capacity, fast, self-reliant of working memory and cognitive ability. 116, 117, 119–121

System 2 *System 2* is slow, low capacity, heavily dependent on working memory and related to individual different in cognitive ability. 115–119, 121, 128, 130, 139–141, 146

visuospatial sketchpad *Visuospatial sketchpad* is part of agent's working memory system to setting up and processing visuospatial imagery. 118

WM Working Memory. 8, 10

working memory *Working memory* is a short-term memory with a highly volatile limited amount of memory storage space where the organism stores its currently detected concepts and referenced concepts. v, vi, 7–17, 19–26, 30–51, 54, 55, 59–61, 63, 64, 66, 74–77, 86, 87, 89, 99–108, 110, 114–122, 128, 130, 139–142, 146–149, 151, 152, 154, 155, 157, 180, 182, 183, 185–188, 190–192, 241

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Appendix A

Appendix

A.1 Intuitive Response Explanatory Statements

Explanatory Statement to Participant

September 2015

Explanatory Statement – Group 1: Tertiary Students

Intuitive Response Study

This information sheet is for you to keep

- **Introduction of this Study:**

My name is Mr. Tang Tiong Yew, a PhD student at the School of Information Technology, Monash University Malaysia. This research project investigates a human's intuitive response and the relationship with working, or short-term, memory processing. In this study, a computer program will show you seven English words to read and then it will then show you two words from the list of seven, the fonts will be blurred on purpose; your task is to give your best guess as to what the word is.

- **Objective of the Study:**

The objective of this study is to empirically capture a model of the human intuitive response behaviors with the perspective of working memory processing in different ambiguous situations.

- **Benefit of the Study:**

The benefit of this project is to further understand about the human intuitive response behaviors and their relationship to working memory processing. Therefore, this study will enable the development of an empirical human intuitive response model for advancing intuitive artificial intelligence system development. For example, we can integrate a human intuitive response model into an artificial intelligence agent to suggest context relevant intuitive responses during an ambiguous situation.

- **Notice:**

Participation is purely voluntary and no monetary payment will be made to you who are involved in this study. Furthermore, at your request, we will send you an electronic copy of the published outcomes of the study in the form of a PhD thesis.

- **How to return this form**

Please give the form to the person in charge on site.

・**What does the study involve?**

We are looking for tertiary students that are 18 years old and above to participate in a data collection related to intuitive responses.

・**How much time it takes?**

The whole data collection process will just takes around 10 minutes per person.

・**The Study Data Gathering Process**

Upon completion of the consent form, you will be given a computer user interface so that you will read seven short English words and then guess two blurred words for 20 repeated times. You need to type in your two guesses into the computer user interface given on the screen.

・**Can I Withdraw from this Study?**

This is entirely voluntary based and you are under no obligation to consent to participation. You can withdraw at any point during the study process.

・**Confidentiality**

This is an anonymized data gathering process therefore your participation will not be identifiable in our research outcome.

・**Storage of Data**

The storage of the data collected will comply with the University regulations. A report of the study may be submitted for thesis publication, but your participation will not be identifiable in such report.

・**Result**

If you would like to be informed about the study's findings, please contact Mr. Tang Tiong Yew on [redacted]

If you would like to contact the person in charge about any aspect of this study, please contact the Student Investigator:	If you have a complaint concerning the manner in which this study is being conducted, please contact:
Mr. Tang Tiong Yew Room 2-4-18, School of Information Technology Monash University Malaysia Email: tang.tiong.yew@monash.edu Supervised by: Dr. Simon Egerton Email: simon.egerton@monash.edu	Mr Chua Khong Wai Senior Manager, Research Management Monash Sunway Campus Jalan Lagoon Selatan 46150 Bandar Sunway Selangor Darul Ehsan, Malaysia [redacted]

Consent Form for Participants

September 2015

Explanatory Statement – Group 1: Tertiary Students

Intuitive Response Study

Note: This consent form will remain with Monash researcher for their record keeping

I agree to take part in the Monash University study specified as above. I understand the project explained to me, and I have read the Explanatory Statement, which I keep for my records. I understand that agreeing to take part means that:

- I agree to read seven English words from a computer screen and key in my two guesses of the blurred words in the screen for twenty repeated times.

I understand that my participation is voluntary, that I can choose not to participate in part or all of the project, and that I can withdraw from the research at any point, without being penalised or disadvantaged in any way.
I understand that any data that the researcher collects for use in reports or published findings will not, under any circumstances, contain names or identifying characteristics.
I understand that none of my identifiable information will be collected.
Data collected from this research may be published online for research purpose only.

I had understood all the terms in this consent form and I agree to them.
☐ Yes ☐ No

Participant's Name:

Signature:

Date:

A.2 Intuitive Response Perceived Stress Scale Questionnaire

PERCEIVED STRESS SCALE

Sheldon Cohen

The *Perceived Stress Scale* (PSS) is the most widely used psychological instrument for measuring the perception of stress. It is a measure of the degree to which situations in one's life are appraised as stressful. Items were designed to tap how unpredictable, uncontrollable, and overloaded respondents find their lives. The scale also includes a number of direct queries about current levels of experienced stress. The PSS was designed for use in community samples with at least a junior high school education. The items are easy to understand, and the response alternatives are simple to grasp. Moreover, the questions are of a general nature and hence are relatively free of content specific to any subpopulation group. The questions in the PSS ask about feelings and thoughts during the last month. In each case, respondents are asked how often they felt a certain way.

Evidence for Validity: Higher PSS scores were associated with (for example):

- failure to quit smoking
- failure among diabetics to control blood sugar levels
- greater vulnerability to stressful life-event-elicited depressive symptoms
- more colds

Health status relationship to PSS: Cohen et al. (1988) show correlations with PSS and: Stress Measures, Self-Reported Health and Health Services Measures, Health Behavior Measures, Smoking Status, Help Seeking Behavior.

Temporal Nature: Because levels of appraised stress should be influenced by daily hassles, major events, and changes in coping resources, predictive validity of the PSS is expected to fall off rapidly after four to eight weeks.

Scoring: PSS scores are obtained by reversing responses (e.g., 0 = 4, 1 = 3, 2 = 2, 3 = 1 & 4 = 0) to the four positively stated items (items 4, 5, 7, & 8) and then summing across all scale items. A short 4 item scale can be made from questions 2, 4, 5 and 10 of the PSS 10 item scale.

Norm Groups: L. Harris Poll gathered information on 2,387 respondents in the U.S.

Norm Table for the PSS 10 item inventory

Category	N	Mean	S.D.
Gender			
Male	926	12.1	5.9
Female	1406	13.7	6.6
Age			
18-29	645	14.2	6.2
30-44	750	13.0	6.2
45-54	285	12.6	6.1
55-64	282	11.9	6.9
65 & older	296	12.0	6.3
Race			
white	1924	12.8	6.2
Hispanic	98	14.0	6.9
black	176	14.7	7.2
other minority	50	14.1	5.0

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Perceived Stress Scale

The questions in this scale ask you about your feelings and thoughts **during the last month**. In each case, you will be asked to indicate by circling *how often* you felt or thought a certain way.

Name ____ Date _________

Age ________ Gender (*Circle*): **M F** Other ___________________________________

0 = Never 1 = Almost Never 2 = Sometimes 3 = Fairly Often 4 = Very Often

1.	In the last month, how often have you been upset because of something that happened unexpectedly?................................	**0**	**1**	**2**	**3**	**4**
2.	In the last month, how often have you felt that you were unable to control the important things in your life?..	**0**	**1**	**2**	**3**	**4**
3.	In the last month, how often have you felt nervous and "stressed"?	**0**	**1**	**2**	**3**	**4**
4.	In the last month, how often have you felt confident about your ability to handle your personal problems?	**0**	**1**	**2**	**3**	**4**
5.	In the last month, how often have you felt that things were going your way?..	**0**	**1**	**2**	**3**	**4**
6.	In the last month, how often have you found that you could not cope with all the things that you had to do?	**0**	**1**	**2**	**3**	**4**
7.	In the last month, how often have you been able to control irritations in your life?..	**0**	**1**	**2**	**3**	**4**
8.	In the last month, how often have you felt that you were on top of things?..	**0**	**1**	**2**	**3**	**4**
9.	In the last month, how often have you been angered because of things that were outside of your control?.................................	**0**	**1**	**2**	**3**	**4**
10.	In the last month, how often have you felt difficulties were piling up so high that you could not overcome them?	**0**	**1**	**2**	**3**	**4**

Please feel free to use the *Perceived Stress Scale* for your research.

Mind Garden, Inc.

info@mindgarden.com

www.mindgarden.com

References

The PSS Scale is reprinted with permission of the American Sociological Association, from Cohen, S., Kamarck, T., and Mermelstein, R. (1983). A global measure of perceived stress. *Journal of Health and Social Behavior, 24,* 386-396.

Cohen, S. and Williamson, G. Perceived Stress in a Probability Sample of the United States. Spacapan, S. and Oskamp, S. (Eds.) *The Social Psychology of Health.* Newbury Park, CA: Sage, 1988.

A.3 Intuitive Response State-Trait Anxiety Inventory Questionnaire

State Trait Anxiety Inventory

Read each statement and select the appropriate response to indicate how you feel right now, that is, at this very moment. There are no right or wrong answers. Do not spend too much time on any one statement but give the answer which seems to describe your present feelings best.

1	2	3	4
Not at all	**A little**	**Somewhat**	**Very Much So**

1. I feel calm	1	2	3	4
2. I feel secure	1	2	3	4
3. I feel tense	1	2	3	4
4. I feel strained	1	2	3	4
5. I feel at ease	1	2	3	4
6. I feel upset	1	2	3	4
7. I am presently worrying over possible misfortunes	1	2	3	4
8. I feel satisfied	1	2	3	4
9. I feel frightened	1	2	3	4
10. I feel uncomfortable	1	2	3	4
11. I feel self confident	1	2	3	4
12. I feel nervous	1	2	3	4
13. I feel jittery	1	2	3	4
14. I feel indecisive	1	2	3	4
15. I am relaxed	1	2	3	4
16. I feel content	1	2	3	4
17. I am worried	1	2	3	4
18. I feel confused	1	2	3	4
19. I feel steady	1	2	3	4
20. I feel pleasant	1	2	3	4

References:

Background:

The STAI is a validated 20 item self report assessment device which includes separate measures of state and trait anxiety. The original STAI form was constructed by Charles D. Spielberger, Richard L. Gorsuch, and Robert E. Lushene in 1964. The STAI has been adapted in more than 30 languages for cross-cultural research and clinical practice (Sesti, 2000). Various reliability and validity tests have been conducted on the STAI and have provided sufficient evidence that the STAI is an appropriate and adequate measure for studying anxiety in research and clinical settings (Sesti, 2000). McIntrye, McIntyre, and Silverio (in press) validated the STAI for Portuguese communities. Several items on the STAI were reversed coded (Items 1, 2, 5, 8, 11, 15, 16, 19, 20).
Recommended for studying anxiety in research and clinical settings.

Developers:

Charles D. Spielberger, Richard L. Gorsuch, and Robert E. Lushene in 1964

Copyright:

Consulting Psychologists Press, Inc.

Reliability:

The stability of the STAI scales was assessed on male and female samples of high school and college students for test-retest intervals ranging from one hour to 104 days. The magnitude of the reliability coefficients decreased as a function of interval length. For the Trait-anxiety scale the coefficients ranged from .65 to .86, whereas the range for the State-anxiety scale was .16 to .62. This low level of stability for the State-anxiety scale is expected since responses to the items on this scale are thought to reflect the influence of whatever transient situational factors exist at the time of testing.

Assessment:

Spielberger, C. D. (1972). *Anxiety: Current trends in theory and research: I.* New York, N.Y.: Academic Press.

Spielberger, C. D. (1980). *Test Anxiety Inventory. Preliminary professional manual*. Palo Alto, CA: Consulting Psychologists Press.

Spielberger, C. D. (1983). *Manual for the State-Trait Anxiety Inventory (STAI)*. PaloAlto, CA: Consulting Psychologists Press.

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A.4 The Life Experiences Survey Questions

These questions at below are extracted from Irwin G. Sarason et al. work [144] of the Life Experiences Survey. These questions had been included into the python program for intuitive response experiment data captures in Chapter 6.

Select only one of the most appropriate rating of your feeling regarding your life experiences. 1:extremely negative, 2:moderately negative, 3:somewhat negative, 4:no impact, 5:slightly positive, 6: moderately positive, 7:extremely positive

Question for adult test participants:

1. Marriage
2. Detention in jail or comparable institution
3. Death of spouse
4. Major change in sleeping habits (much more or much less sleep)
5. Death of close family member: mother
6. Death of close family member: father
7. Death of close family member: brother
8. Death of close family member: sister
9. Death of close family member: grandmother
10. Death of close family member: grandfather
11. Death of close family member: other (specify)
12. Major change in eating habits (much more or much less food intake)
13. Foreclosure on mortgage or loan
14. Death of close friend
15. Outstanding personal achievement
16. Minor law violation (traffic tickets, disturbing the peace, etc.)
17. Male: Wife/girlfriend's pregnancy
18. Female: Pregnancy

19. Changed work situation (different work responsibility, major change in working conditions, working hours, etc.)
20. New job
21. Serious illness or injury of close family member: father
22. Serious illness or injury of close family member: mother
23. Serious illness or injury of close family member: sister
24. Serious illness or injury of close family member: brother
25. Serious illness or injury of close family member: grandfather
26. Serious illness or injury of close family member: grandmother
27. Serious illness or injury of close family member: spouse
28. Serious illness or injury of close family member: other (specify)
29. Sexual difficulties
30. Trouble with employer (in danger of losing job, being suspended, demoted, etc.)
31. Trouble with in-laws
32. Major change in financial status (a lot better off or a lot worse off)
33. Major change in closeness of family members (increased or decreased closeness)
34. Gaining a new family member (through birth, adoption, family member moving in, etc.)
35. Change of residence
36. Marital separation from mate (due to conflict)
37. Major change in church activities (increased or decreased attendance)
38. Marital reconciliation with mate
39. Major change in number of arguments with spouse (a lot more or a lot less arguments)

40. Married male: Change in wife's work outside the home (beginning work, ceasing work, changing to a new job, etc.)
41. Married female: Change in husband's work (loss of job, beginning new job, retirement, etc.)
42. Major change in usual type and/or amount of recreation
43. Borrowing more than RM450,000 (buying home, business, etc.)
44. Borrowing less than RM450,000 (buying car, TV, getting school loan, etc.)
45. Being fired from job
46. Male: Wife/girlfriend having abortion
47. Female: Having abortion
48. Major personal illness or injury
49. Major change in social activities, e.g., parties, movies, visiting (increased or decreased participation)
50. Major change in living conditions of family (building new home, deterioration of home, neighborhood, etc.)
51. Divorce
52. Serious injury or illness of close friend
53. Retirement from work
54. Son or daughter leaving home (due to marriage, college, etc.)
55. Ending of formal schooling
56. Separation from spouse (due to work, travel, etc.)
57. Engagement
58. Breaking up with boyfriend/girlfriend
59. Leaving home for the first time
60. Reconciliation with boyfriend/girlfriend

Question for student test participants:

1. Beginning a new school experience at a higher academic level (college, graduate school, professional school, etc.)
2. Changing to a new school at same academic level (undergraduate, graduate, etc.)
3. Academic probation
4. Being dismissed from dormitory or other residence
5. Failing an important exam
6. Changing a major
7. Failing a course
8. Dropping a course
9. Joining a fraternity/sorority
10. Financial problems concerning school (in danger of not having sufficient money to continue)

A.5 Long-Term Memory Content Test

The *long-term memory content test* is similar to Lupien et al. [106] test for priming long-term information into the test subject's reference memory. The list below is the 12 pairs of words for this test. This test will repeat 4 times and each time the test subject need to recall all the 12 pairs of words and key-in the answers into the given form on the screen.

1. bus crash
2. dead cat
3. burning tree
4. bridge collapse
5. dog bite
6. car thief

7. road block
8. time bomb
9. thunder strike
10. police arrest
11. shark attack
12. hidden camera

A.6 Short-Term Memory Content Test

The *short-term memory content test* is inspired from Frederick's Cognitive Reflection Test (CRT) [57] and Sternberg test [159]. This test is for priming short-term information into the test subject's working memory. The following list is the 10 rows of 7 words for this test. Two words will be randomly selected to be blurred for the test subject to guess. Then, the test subject need to key-in the answers into the given form on the screen.

1. library, love, buses, park, crash, hotdog
2. bicycle, dead, time, lecturer, cat, bomb
3. panda, jungle, burn, house, trees, waterfall
4. beach, bird, bite, balloon, dog, boat
5. storm, strikes, thunder, dolphin, moon, plane
6. cable, hidden, collapsed, camera, bridges, basket
7. chip, car, window, book, train, thief
8. cook, smoke, road, wine, stage, block
9. bomb, police, drink, smoke, arrested, belt
10. attacking, worm, king, soap, shark, walk

A.7 Intuitive Response Questionnaire Result

No	S1-1	S1-2	S1-3	S1-4	S1-5	S1-6	S1-7	S1-8	S1-9	S1-10	S2-1	S2-2	S2-3	S2-4	S2-5	S2-6	S2-7	S2-8	S2-9	S2-10	S2-11	S2-12	S2-13	S2-14	S2-15	S2-16	S2-17	S2-18	S2-19	S2-20	S3-1	S3-2	S3-3	S3-4	S3-5	S3-6	S3-7	S3-8	S3-9	S3-10	S3-11	S3-12	S3-13	S3-14	S3-15	S3-16	S3-17	S3-18	S3-19	S3-20
1	3	1	2	0	2	4	2	0	3	2	3	3	2	2	3	1	1	3	2	1	4	1	1	2	3	3	1	1	3	1	3	3	3	2	2	1	1	3	2	2	3	2	2	1	2	3	2	2	4	2
2	2	1	2	3	3	2	3	2	2	2	3	4	2	3	3	2	1	3	1	1	3	2	2	2	3	2	2	4	3	3	3	3	2	2	3	2	1	3	2	1	3	1	2	1	3	2	2	1	3	3
3	2	2	2	3	3	2	2	2	2	2	4	4	3	2	4	3	3	2	3	2	3	2	2	3	3	3	2	2	3	3	2	3	3	3	3	3	3	3	3	2	3	3	3	2	3	3	3	3	3	2
4	2	0	1	3	3	0	2	3	1	0	4	4	1	1	4	1	1	3	1	1	3	1	1	1	4	3	1	1	3	3	3	3	3	2	3	2	1	1	1	1	2	1	1	2	2	2	1	1	3	3
5	3	3	3	2	2	3	2	2	3	3	2	3	3	2	2	2	2	2	2	1	2	1	1	1	2	2	2	2	2	2	2	3	1	1	2	1	2	3	1	1	3	1	1	1	2	1	1	1	2	2
6	2	3	4	2	2	3	4	2	2	2	2	3	2	2	2	1	3	2	1	1	2	2	2	1	3	3	3	2	3	2	3	3	2	2	3	1	3	2	1	1	2	2	1	2	2	3	3	2	2	3
7	2	2	3	3	3	2	2	3	1	2	3	3	3	3	2	1	3	3	1	2	4	3	2	2	4	4	2	2	4	4	3	3	1	1	4	1	2	4	1	3	4	2	2	3	4	4	1	1	4	4
8	2	1	2	3	2	1	3	3	1	1	3	3	2	2	3	3	1	3	1	1	3	1	1	1	3	3	1	1	3	3	3	3	2	2	3	2	1	3	1	1	3	1	1	3	3	3	1	1	3	3
9	1	1	1	4	3	1	3	3	1	1	3	4	2	1	3	2	2	3	1	1	4	2	1	2	3	3	2	1	4	3	4	4	3	1	4	2	1	3	1	1	4	2	1	1	4	4	2	1	4	3
10	1	1	2	3	3	1	2	3	1	0	4	4	1	1	4	1	1	3	1	1	4	1	1	1	4	3	1	1	4	3	4	4	1	1	4	1	1	4	1	4	4	1	1	1	4	3	1	1	4	3
11	1	1	2	3	4	0	4	4	0	1	4	4	1	1	4	1	1	3	1	1	4	1	1	1	4	4	1	1	4	4	4	4	2	1	3	1	1	4	1	1	4	1	1	1	4	4	1	1	4	4
12	1	2	2	1	3	2	3	3	1	3	4	4	1	2	4	1	3	3	1	1	3	1	2	2	4	4	1	1	4	4	4	4	2	2	3	3	2	4	1	1	3	1	2	3	4	4	1	1	4	4
13	2	1	3	4	3	2	2	2	1	0	4	4	1	1	4	1	2	3	1	1	3	1	1	1	4	4	1	1	4	4	4	2	3	3	2	4	1	1	1	2	2	1	1	2	2	1	1	1	3	2
14	0	0	0	4	4	0	3	3	0	0	4	4	1	1	4	1	4	4	1	1	4	1	1	1	4	4	1	1	4	4	4	4	1	1	4	1	1	4	1	1	4	1	1	1	4	4	1	1	4	4
15	2	2	3	3	4	3	3	3	1	2	3	4	1	4	1	1	1	3	1	1	3	1	1	1	3	3	1	1	3	3	3	3	1	2	1	1	1	2	1	1	2	1	1	1	3	3	1	1	3	3
16	1	2	3	2	2	3	2	2	3	2	3	3	2	2	2	1	3	3	3	2	3	3	3	2	2	3	3	2	2	2	4	3	2	2	3	2	2	3	2	1	3	2	2	2	3	3	2	2	3	3
17	2	1	2	4	4	2	1	2	1	2	3	3	2	3	2	2	2	2	1	2	3	1	1	1	3	3	2	2	3	3	3	3	2	3	3	1	2	3	1	2	3	1	1	1	3	3	2	2	3	3
18	4	4	4	2	2	3	0	2	3	3	4	4	1	1	4	1	1	3	1	1	2	1	1	1	3	3	1	1	3	3	4	4	1	1	4	1	1	3	1	1	3	1	1	1	4	3	1	1	4	3
19	1	2	2	2	3	1	4	2	1	2	4	4	1	1	3	1	1	3	1	1	3	1	1	1	4	4	1	1	4	4	3	4	2	1	3	2	1	3	1	1	3	1	1	1	4	3	1	1	4	4
20	2	3	2	3	2	2	3	3	2	2	4	3	2	1	4	2	3	3	2	2	4	1	1	2	4	3	2	1	4	3	4	3	2	1	4	2	3	4	2	2	4	1	2	2	3	2	1	1	4	3
21	2	1	2	3	3	0	3	2	1	0	4	4	1	1	3	1	1	3	1	1	3	1	1	1	4	3	1	1	4	4	4	4	1	1	3	1	1	3	1	1	3	2	1	1	3	2	1	1	4	4
22	2	2	3	1	2	2	2	1	2	3	3	4	3	2	2	2	4	2	3	1	3	2	2	2	4	3	3	3	3	2	2	2	3	3	3	1	2	4	1	1	3	1	3	2	4	2	1	1	3	3
23	3	3	3	3	3	3	3	2	2	3	3	3	2	2	3	1	2	2	1	1	3	2	1	1	2	2	1	1	2	3	2	3	2	2	3	2	2	3	1	1	2	2	1	1	4	3	1	2	3	3
24	2	1	3	4	1	1	4	2	3	2	4	3	2	2	4	1	1	4	1	1	3	1	1	2	4	4	1	1	3	4	4	4	1	1	3	1	2	4	1	1	4	2	1	1	3	4	1	1	4	4
25	1	2	2	1	3	2	3	1	2	1	3	3	1	1	3	1	1	2	1	1	2	1	1	2	3	3	1	1	3	3	2	3	2	3	3	1	1	2	1	1	2	1	1	2	3	3	1	1	3	3
26	2	3	2	3	3	2	3	3	1	2	4	3	3	1	3	1	1	2	1	2	3	3	2	2	3	3	1	1	3	2	3	3	2	2	2	2	1	2	1	1	3	2	1	2	3	3	1	1	2	2
27	3	3	4	3	2	3	3	3	3	3	3	3	3	2	3	1	2	3	1	2	3	1	1	3	3	3	3	1	3	3	3	3	2	3	3	1	1	3	1	1	4	1	1	2	2	3	3	2	3	3
28	3	2	2	2	3	2	1	2	4	3	4	4	2	1	3	3	1	3	1	1	3	2	1	4	3	1	2	1	2	4	1	3	4	3	3	3	3	2	1	1	2	2	1	4	2	1	2	3	2	3
29	1	2	2	3	3	2	3	3	1	1	3	3	1	1	3	1	1	3	1	1	3	1	1	1	3	1	1	1	3	3	3	3	1	1	3	1	1	3	1	1	3	1	1	1	3	3	1	1	3	3
30	1	0	1	4	3	1	4	4	1	1	4	4	1	1	4	2	1	4	1	1	4	1	1	2	4	3	1	1	4	1	2	2	3	3	3	2	1	2	1	2	2	1	1	1	2	1	2	1	1	1
31	4	4	4	1	2	2	1	1	4	4	1	2	3	3	1	2	4	2	1	4	2	1	1	4	1	1	3	3	1	1	1	3	4	4	1	1	3	1	1	4	1	3	3	4	1	1	4	3	1	2
32	2	3	3	2	2	2	3	2	1	1	2	4	3	2	3	1	2	3	1	1	2	2	2	3	2	3	2	3	2	3	1	2	4	4	2	1	2	1	1	1	3	3	3	2	2	1	1	1	2	2

Figure A.1: Intuitive Response Questionnaire Result.

A.8 Long-Term Memory Test Result

A.9 Long-Term Memory Test Result Part 1

No	S	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q11	Q12	Q13	Q14	Q15	Q16	Q17	Q18	Q19	Q20	Q21	Q22	Q23	Q24	Q25	Q26	Q27	Q28	Q29	Q30
1	F	z	z	z	b3	z	z	z	z	z	z	/2	z	z	z	z	z	z	z	b2	z	/2	z	z	z	z	z	z	z	z	z
2	F	/6	z	z	z	z	z	z	z	/4	z	z	z	z	z	/7	z	/5	z	/6	z	z	z	z	z	z	z	z	z	z	z
3	F	z	z	z	z	z	z	z	z	z	z	z	/3	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z
4	F	z	z	z	z	z	z	z	z	z	z	b2	z	z	z	z	z	z	z	/7	/7	z	z	z	z	z	z	z	z	z	z
5	F	/5	z	z	b5	/1	z	z	z	/1	/1	/3	b3	b4	z	b6	z	z	z	b6	b6	z	/1	z	z	/1	/1	b3	b2	z	b3
6	F	b7	z	z	z	z	z	z	z	z	z	b1	z	z	z	z	z	z	z	b6	z	z	z	z	z	z	z	z	z	z	z
7	F	/6	z	z	z	z	z	z	z	z	z	z	z	z	z	/6	z	z	z	/3	z	z	z	z	z	z	z	z	z	z	z
8	F	z	z	z	z	z	z	z	z	z	z	/5	z	z	/3	/6	/5	/7	z	/3	z	/3	z	z	/3	z	z	z	z	z	z
9	F	b4	z	z	b3	z	z	z	z	z	z	z	z	z	z	b6	z	z	z	b6	z	z	z	z	z	z	z	z	z	z	z
10	F	z	z	z	z	z	z	z	z	z	z	z	z	z	z	/7	z	z	z	/7	z	z	z	z	z	z	z	z	z	z	z
11	F	z	z	z	/3	z	z	z	z	z	z	z	/3	z	z	/6	z	z	z	/3	z	z	z	z	z	z	z	z	z	z	/3
12	T	z	b7	z	z	z	z	z	z	b6	z																				
13	T	z	z	b2	z	z	z	z	z	b4	b2																				
14	F	z	z	z	z	z	z	z	z	z	z	z	z	z	z	/6	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z
15	T	z	z	z	z	z	z	z	z	/6	/3																				
16	T	z	z	z	z	z	z	z	z	/6	z																				
17	F	z	z	z	b3	z	z	z	z	z	z	z	z	z	z	b6	z	z	z	b5	z	z	z	z	z	z	z	z	z	z	z
18	T	/7	z	b3	z	z	z	z	z	b5	z																				
19	F	/3	z	z	/2	z	z	z	z	z	z	z	b5	z	z	b4	z	z	z	/6	/6	z	z	z	z	z	z	z	z	z	z
20	F	z	z	z	b6	z	z	z	z	z	z	z	z	z	z	z	b3	z	z	z	b4	z	z	z	z	z	z	z	z	z	b5
21	F	/7	z	z	z	z	z	z	z	z	z	z	b5	z	z	b5	z	z	z	z	z	b3	b3	z	z	z	z	z	z	z	z
22	F	z	z	z	/3	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z
23	F	/6	z	z	b1	b1	z	z	z	z	b1	b1	z	z	z	b7	z	z	z	b2	b5	z	z	z	z	z	b3	z	b1	z	b2
24	T	/3	z	z	z	z	z	z	z	z	b7																				
25	T	z	z	z	z	z	z	z	z	b6	z																				
26	T	z	z	z	z	z	z	z	z	/6	z																				
27	T	z	z	z	z	z	z	z	z	/7	z																				
28	T	/7	/6	z	z	/1	b4	z	z	b7	b2																				
29	F	b6	z	z	z	z	z	z	z	z	z	z	z	b6	z	b7	z	b7	b7	z	z	z	z	z	z	z	z	z	z	z	z
30	F	z	/3	z	z	z	z	z	z	z	z	z	z	z	/3	z	/4	z	z	z	z	z	z	z	z	z	z	z	z	z	z
31	F	b2	z	z	b3	z	z	z	z	/2	z	b3	b6	z	b5	z	b1	z	z	b3	z	z	z	z	z	z	z	z	/3	z	z
32	F	z	z	z	/6	z	z	z	z	/4	z	z	z	z	z	/6	/3	z	z	z	/1	z	z	z	z	z	z	z	b3	z	z

No	Q31	Q32	Q33	Q34	Q35	Q36	Q37	Q38	Q39	Q40	Q41	Q42	Q43	Q44	Q45	Q46	Q47	Q48	Q49	Q50	Q51	Q52	Q53	Q54	Q55	Q56	Q57	Q58	Q59	Q60
1	z	b1	b2	z	z	z	b2	z	z	z	z	b5	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z
2	z	/3	z	/6	z	z	z	z	/3	/3	z	/4	z	/3	z	z	z	z	/3	z	z	z	z	z	b5	z	z	z	z	z
3	z	z	z	/6	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z
4	/6	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	/3	z	z	z	z	z	z	z	z	z	z	z
5	z	b2	/3	b2	z	z	z	z	b5	z	z	z	z	z	/5	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z
6	z	b3	z	z	b5	z	z	z	z	z	z	z	z	z	z	z	z	b1	b3	z	z	b1	z	z	z	z	b3	b2	b5	z
7	z	z	z	/7	/6	z	z	z	b3	z	z	z	z	z	z	z	z	z	/5	z	z	z	z	z	z	z	/7	z	/4	z
8	z	z	z	/6	z	z	z	z	z	/6	z	z	z	z	/4	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z
9	z	b3	b3	z	z	z	z	z	b4	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z
10	z	/7	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z
11	z	/2	z	z	z	z	z	z	z	z	z	z	z	/3	z	z	z	z	/4	z	z	z	z	z	z	z	z	z	z	z
12																														
13																														
14	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z
15																														
16																														
17	z	b3	b1	z	/3	b1	z	z	z	z	z	b6	z	z	z	z	z	b1	b6	z	z	z	z	z	z	b6	z	z	b3	z
18																														
19	z	b3	z	z	/5	z	z	z	z	z	z	b5	z	b3	z	z	z	z	b6	b3	z	z	z	z	z	z	z	z	z	z
20	z	b3	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	b3	z	z	z	z	z	z	z	z	z	z	z
21	z	z	/7	b7	z	z	z	z	z	z	z	z	z	z	z	z	z	z	b5	z	z	z	z	z	z	z	z	z	z	z
22	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	/2	z	z	z	z	z	z	z	z	z	z	z	z
23	z	b3	z	z	z	z	z	z	b3	z	z	z	z	z	z	z	z	z	b5	z	z	z	z	z	z	b3	z	z	z	z
24																														
25																														
26																														
27																														
28																														
29	z	z	z	b7	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z
30	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z
31	z	b3	b2	/6	z	z	b2	z	z	z	z	b6	z	b4	z	z	z	z	b5	z	z	z	z	z	z	z	z	b1	z	z
32	z	b7	b7	z	z	z	z	z	z	z	z	z	z	b6	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z	z

Figure A.2: Long-Term Memory Test Result Part 1.

A.10 Long-Term Memory Test Result Part 2

R1-A1	R1-A2	R1-A3	R1-A4	R1-A5	R1-A6	R1-A7	R1-A8	R1-A9	R1-A10	R1-A11	R1-A12	TIME	P
thunder strike	police arre	bridge collap	time bomb									48.53404	4
car crash	thunder str	road block	tree colapse	dog bite	cat tree							97.29067	3
hidden camera	bus crash	dog bite	shark attack	police arrest	cat							46.32395	5
bus crash	time bomb	thunder strike	police arrest									61.84575	4
time bomb	car crash	police xx	dog xx									63.78547	1
car thief												23.96664	1
bus crash												11.12074	1
car crush												55.12688	0
hidden camera	shark attac	bush burning	police arrest	bomb blast	car theft							92.59904	3
bus crash	dead cat	burning tree	collapsed bric	dig bite								55.50241	3
hidden camera	dog bite	cat dead	shark attack	burning tree	bus crash	road block						72.37416	6
hidden camera	car crash	burning tree	dead cat									35.98634	3
bus crash	shark attac	time bomb	dog cat									45.48527	3
hidden camera	bus crash											24.03569	2
bus crash												12.74185	1
bus crash	hidden can	thunder strike										26.1021	3
hidden camera	police arre	thunder strike	tree burn	cat	dog bite							66.81596	4
car crash	police	thunder strike	dog bites	bridge	tree	thief	hidden camer	fire				125.2356	2
car crash	dog bite	shark attack	time bomb	police arrest	thunder strike							55.13875	5
hidden camera	dog bite	house burn	road block	burning tree	shark attack	car thief						66.52911	6
hidden camera	bus stop	thunder strike	police	cat fight								112.1459	2
thunder strike	bus crash	thief	traffic light	thunder storm	time bomb	car crash						99.38985	2
bus crash												9.208948	1
hidden camera	dead cat	bridge collap	road block	shark attack	dog bite							60.69773	6
hidden camera	police arre	shark attack	time bomb									41.22442	4
shark attack												7.376513	1
bus crash	hidden can	shark attack	car thief	stolen cat								74.67464	4
hidden camera	bus crash											56.62167	2
hidden camera	bus crash	dog theif										37.08746	2
dog bite	police arrest											61.8133	2
bus crash	road block	bridge burn	dog bite	cat attack	traffic jam	fallen tree	burning car					58.35751	3
dog bite	bus crash											33.31335	2

R2-A1	R2-A2	R2-A3	R2-A4	R2-A5	R2-A6	R2-A7	R2-A8	R2-A9	R2-A10	R2-A11	R2-A12	TIME	P
police arrest	road block	time bomb	shark attack	dog bite	dead cat	bus crash						47.43487	7
car crash	cat tree	dog bite	police arrest	shark attack	road block	thunder strike	time bomb					56.82616	6
hidden camer	shark attack	police arrest	dog bite	burning tree	dead cat	bus crash	car					72.31793	7
car thief	time bomb	dead cat	thunder strike	road block	police arrest							51.85676	6
hidden camer	dog bite	car crash	shark attack	time bomb								53.83483	4
car thief	shark attack	hidden camer	dog bite									55.36623	4
shark attach	bus crash	road block	bridge collap	hidden camer	dog bite							40.4882	5
police arrest	hidden camer	truck crash	hidden camer	dog bite								70.61445	3
thunder strike	police arrest	bomb blast	shark attack	hidden camer	road block							120.2314	5
hidden camer	car thief	road block	police arrest	shark attack	thunder strike	bus crash	dead cat	burning tree	dog bite	colapsed bridge		77.77291	10
car dead	dog bite	police arrest	shark attack	thunder strike	time bomb	road block	car thief	burning tree				114.4916	8
hidden camer	shark attack	police arrest	time bomb	car crash	dead cat	thunder strike						48.99594	6
hidden camer	shark attack	time bomb	dog bite	dead cat	car thief	thunder strike	bus crash	police				74.39562	8
hidden camera												18.02811	1
hidden camer	shark attack	burning tree	lightning stril	car theif	dead cat	road block						56.66623	5
police arrest	shark attack	dead cat	bus crash	hidden camer	burning forest							28.61661	5
hidden camer	shark attack	dead cat	dog bite	police arrest	bus crash	thunder strike	car thief	burning tree				105.1385	9
shark attack	dog bite	bus crash	burning tree	hidden camer	police arrest	bridge collap	thunder strike					105.5917	8
hidden camer	bus crash	dead cat	time bomb	police arrest	shark attack	burning tree	dog bite	road block				91.56005	9
burning tree	shark attack	time bomb	bridge collapse									54.04975	4
hidden camer	shark attack	time bomb	dead cat	road block								69.71006	5
time bomb	police arrest	hidden camer	bus crash	dog bite	thunder strike	car thief						77.17547	7
bus crash	dead cat	burning tree	shark attack	time bomb	police arrest	hidden camera						45.58911	7
shark attack	hidden camer	time bomb	dog bite	thunder strike	bridge collap	road block	police arrest	dead cat	car thief			74.63664	10
bus crash	time bomb	dead rat	police arrest	thunder strike	hidden camera							48.78739	5
shark attack	bus crash	hidden camer	thunder strike	dog bite								25.16867	5
bus crash	hidden camer	time bomb	dead cat	bridge collap	dog bite	police arrest						83.74942	7
police arrest	hidden camer	bus crash	falling tree	car theft								73.92365	3
shark attack	police arrest	dog bite	car theft	hidden camer	time bomb							35.95671	5
hidden camer	dog bite	police arrest	road block	house collaps	fallen tree	bridge collapse						144.422	5
hidden camer	shark attack	dog bite	cat dead	traffic jam	bridge collap	police arrest						56.63485	5
hidden camer	police arrest	dog bite	dead cat	car crash								41.07612	4

Figure A.3: Long-Term Memory Test Result Part 2.

A.11 Long-Term Memory Test Result Part 3

R3-A1	R3-A2	R3-A3	R3-A4	R3-A5	R3-A6	R3-A7	R3-A8	R3-A9	R3-A10	R3-A11	R3-A12	TIME	P
hidden camera	burning tree	police arrest	dead cat	dog bite	road block	thunder strike	time bomb					71.25768	8
bus crash	cat dead	bus collide	dog bite	bridge	shark attack	thunder strike	road block	time bomb	hidden camer	police arrest		107.70664	8
bus crash	dead cat	burning tree	time bomb	hidden camer	dog bite	police arrest	shark attack					86.586566	8
bus crash	dead cat	collapsed bric	hidden camer	police arrest	car thief	thunder strike	time bomb					69.452006	7
hidden camera	police arrest	time bomb	shark attack	cat	bridge							46.550191	4
dog bite	dead cat	bus crash	hidden camer	car thief								43.837934	5
shark attack	hidden camera	time bomb	bus crash	bridge collap	car thief	road block	dog bite	dead cat	burning tree			71.996018	10
shark attack	hidden camera	shark attack	dog bite	truck crash	dog bite	cat nap						67.453508	3
dog bite	bush tree	hidden camer	thunder strike	police arrest	time bomb							117.29582	5
time bomb	car thief	hidden camer	police arest	road block	shark attack	thunder stirke	bus crash	dog bite	dead cat	burning tree	collapsed bridge	107.16942	9
hidden camera	police arrest	hidden camer	thunder strike	road block	time bomb	cat dead	dog bite	burning tree	bridge collap	car thief	bus crash	84.543037	10
hidden camera	road block	thunder strike	dead cat	dog bite	bus crash	police arrest	time bomb	burning tree	shark attack			44.143764	10
hidden camera	shark attack	police arrest	burning tree	dog bite	bridge collap	time bomb	dead cat	bus crash				109.35812	9
hiddebn camera	death cat	sharp attack										25.999717	0
road block	dog bite	bridge collap	hidden camer	thunder strike	car thief	dead cat	burning tree	bus crash	time bomb	shark attack		98.353748	11
bridge collapse	burning tree	car thief	hidden camer	bus crash	dead cat	police arrest	road block	time bomb				74.425433	9
time bomb	bridge collaps	road block	police arrest	dead cat	thunder strike	dog bite	burning tree	hidden camer	car thief			156.42983	10
road block	time boom	dead cat	bus crash	bridge collap	hidden camer	thunder strike	dog bite	burning tree	police arrest			142.1387	9
hidden camera	dog bite	car thief	bridge collap	shark attack	time bomb	road block	police arrest	thunder strike	dead cat	burning tree	bus crash	98.876563	12
bus crash	bridge collaps	time bomb	thunder strike	police arrest	road block	dog bite	hidden camer	burning tree	shark attack	cat dies	time attack	142.68097	10
police arrest	hidden camera	thunder strike	dog bite	bridge collap	bus crash							84.475128	6
hidden camera	car thief	bus crash	dog bite	thunder strike	dead cat	burning tree	road block	bridge collap	police arrest			119.21291	10
bus crash	road block	shark attack	hidden camer	thunder strike	dog bite	bridge collapse	police arrest	burning tree				78.45539	9
bus crash	burning tree	thunder strike	police arrest	road block	dead cat	dog bite	road block	shark attack	time bomb	hidden camera		82.713675	10
hidden camera	shark attack	police arrest	burning tree	car crash	bridge collap	time bomb	road block					96.728383	7
shark attack	hidden camera	police arrest	dead cat	burning tree	thunder strike	bus crash						46.29384	7
hidden camera	shark attack	bus crash	dog bite	road block	bridge collap	dead cat	police arrest	burning tree	thunder strike			89.531425	10
hidden camera	bus crash	burning tree	shart attack	time bomb	dog bite	falling bridge						97.786479	5
hidden camera	dog bite	thunder strike	car theif	police arrest	time bomb							38.629624	5
hidden camera	road block	dead cat	shark attack	police arrest	car crash	bridge collapse	road block	car crash	fallen tree	dog bite		186.45983	7
hidden camera	shark attack	time bomb	bus crash	dead cat	dog bite	bridge collapse	road block	traffic jam	police arrest			87.386798	9
dog bite	dead cat	car crash	police arrest	hidden camer	thunder strike	burning tree	time bomb					87.774946	7

R4-A1	R4-A2	R4-A3	R4-A4	R4-A5	R4-A6	R4-A7	R4-A8	R4-A9	R4-A10	R4-A11	R4-A12	TIME	P
thunder strike	time bomb	police arrest	burning tree	dead cat	dog bite	shark attack	bridge collap	road block	hidden camera			333.80725	10
tree burn	cat dead	car thief	dog bite	road block	police arrest	bridge collap	thunder strik	shark attack	hidden came	bus crash	time bomb	301.02701	10
hidden camera	bus crash	police arrest	dog bite	dead cat	thunder storr	shark attack	time bomb	burning tree	bridge collapse			311.33351	9
time bomb	thunder strik	police arrest	burning tree	dead cat	bus crash	collapsed bri	hidden came	car thief	shark attack	dog bite		308.44437	10
shark attack	police arrest	time bomb	bridge collap	hidden came	dog bite							278.98431	6
bus crash	dead cat	dog bite	shark attack	hidden came	car theif	time bomb						306.74107	6
dog bite	thunder strik	dead cat	burning tree	bridge collap	police arrest	road block	time bomb	shark attack				305.07943	9
burning bridges	police arrest	dog bite	hidden came	dead cat	plane crash							417.62063	4
police arrest	time bomb	thurder strike	dog bite	car thieve	bridge collap	bush tree						398.14746	4
hidden camera	bridge collap	shark attack	thunder strik	car thief	road block	police arrest	time bomb	bus crash	dead cat	dog bite	burning tree	327.47179	12
time bomb	thunder strik	dog bite	cat dead	bus crash	burning tree	shark attack	car thief	road block	police arrest			358.67999	9
time bomb	shark attack	lightning strik	dog bite	dead cat	burning tree	police arrest	bus crash	car thief				250.6406	8
bus crash	dead cat	bridge collaps	dog bite	road block	car thief	police arrest	thunder strik	hidden came	shark attack	burning tree		283.0627	11
cat	shark attack											259.83359	1
shark attack	bridge collap	burning tree	car theif	dog bite	dead cat	time bomb	hidden came	thunder strik	police arrest			332.24073	9
dead cat	bus crash	shark attack	hidden came	thunder strik	burning tree	dog bite	time bomb	bridge collapse				262.94474	9
dead cat	thunder strik	dog bite	hidden came	burning trees	car thief	police arrest	road block	bus crash	shark attack			637.65722	9
shark attack	time boom	hidden camera	burning tree	bus crash	dog bite	dead cat	thunder strik	road block	police arrest	bridge collapse		318.1457	10
thunder strikes	bus crash	dead cat	road block	car thief	dog bite	shark attack	hidden came	police arrest	time bomb	school closure		358.67366	9
burning tree	bridge collap	car thief	time bomb	thunder strik	hidden came	dog bite	bus crash	police arrest	cat dies	road block	tiem machine	381.73293	10
hidden camera	thunder strik	time bomb	police	dog bite	bridge collap	bus crash	tree					382.11896	5
bus crash	dead cat	time bomb	thunder strik	bridge collap	pollice arrest	dog bite	hidden came	shark attack	burning tree	road block	car crash	387.11401	10
bus crash	dead cat	burning tree	bridge collap	road block	car thief	hidden came	police arrest	time bomb	thunderstrike	dog bite		345.18114	10
bus crash	burning tree	thunder strike	dead cat	dog bite	police arrest	road block	time bomb	hidden came	shark attack	car thief		272.2701	11
hidden camera	time bomb	dead cat	shark attack	car crash	police arrest	bridge collap	thunder strik	road block				293.45043	8
bus crash	dead cat	thunder strike	road block	collapsed bri	dog bite	police arrest	shark attack	hidden camera				210.71317	8
hidden camera	raod block	bus crash	dog bite	shark attack	thunder strik	birdge collap	time bomb	police arrest	burning tree	dead cat		366.80243	9
hidden camera	brigde falling	thunder strike	burning tree	dead cat	dog bite	shart attack	car accident					358.34095	5
thunder storm	car theif	police arrest	dog bite	bus crash								248.07115	3
collapse bridge	road block	police arrest	dog bite	bus crash	hidden came	fallen tree						717.55701	5
bus crash	dead cat	collapsed brid	dog bite	burning tree	road block	traffic jam	shark attack	hidden came	time bomb			264.35952	8
thunder strike	time bomb	dead cat	dog bite	car theif	bus crash	burning tree	hidden came	police arrest				294.90928	8

Figure A.4: Long-Term Memory Test Result Part 3.

A.12 Short-Term Memory Test Result

A.13 Short-Term Memory Test Result Part 1

No	T1-A1	T1-A2	T1-C1	T1-C2	TIME	T2-A1	T2-A2	T2-C1	T2-C2	TIME	T3-A1	T3-A2	T3-C1	T3-C2	TIME	T4-A1	T4-A2	T4-C1	T4-C2	TIME
1	par	over	park	love	7.721174	dead	lecturer	dead	lecturer	6.083518	house	trees	house	trees	49.995468	boat	beach	boat	beach	3.323372
2	hotdog	buses	hotdog	buses	24.177983	time	time	time	bomb	12.691661	house	waterfall	house	waterfall	9.733583	boat	bird	boat	bird	7.940586
3	hotdog	park	hotdog	park	15.375291	time	bicycle	time	bicycle	10.250821	panda	jungle	panda	jungle	8.615916	dog	bite	dog	bite	11.605721
4	park	library	park	library	16.982236	lecture	dead	lecturer	dead	19.965695	house	panda	house	panda	8.846439	bird	bite	bird	bite	20.652714
5		library	park	library	40.169056	dead	lecturer	dead	lecturer	8.771895	jungle	burn	jungle	burn	11.106334	boat	jungle	boat	balloon	11.269225
6		park	hotdog	park	29.830227	cat	bicycle	cat	bicycle	11.818711	waterfall	jungle	waterfall	jungle	10.897615	bird	dog	bird	dog	7.602757
7	buses	park	buses	crash	17.655867	dead	cat	dead	cat	7.52508	tress	burn	trees	burn	8.678099	beach	balloon	beach	balloon	14.806802
8	crash	love	crash	love	38.894829	dead	bicycle	dead	lecturer	19.18332	jungle	trees	jungle	trees	14.3971	bite	ballon	bite	balloon	14.505247
9	crash	love	crash	love	39.959155	dead	bicycle	dead	bicycle	15.279617	panda	waterfal	panda	waterfall	14.840079	bite	beach	bite	beach	10.341439
10	park	over	park	love	30.838384	dead	cat	dead	cat	8.945266	burning	trees	house	trees	15.948366	block	road	boat	bird	12.857586
11			library	crash	15.212521		lecture	bicycle	lecturer	34.156819	tree	jungle	trees	jungle	18.688329	boat	bite	boat	bite	8.82148
12	park	crash	park	crash	12.263243			bomb	lecturer	2.310418	jungle	burn	jungle	burn	6.371118	boat	beach	boat	bite	10.86575
13	library	crash	library	crash	8.372967	dead	bomb	dead	bomb	4.540017	trees	jungle	trees	jungle	4.26062	dog	boat	dog	boat	3.64492
14	crash		crash	park	6.69257	time bomb		time	bomb	6.881075	turn		trees	burn	8.060872	dog		balloon	dog	5.751103
15	library		library	love	14.773928	cat	bomb	cat	bomb	7.585522	waterfal	tree	waterfall	burn	19.642527	bite	bird	bite	bird	22.724567
16	buses	hotdog	buses	hotdog	21.71283	lecturer	bomb	lecturer	dead	7.411986	jungle	house	jungle	house	3.895534	beach	baloon	beach	balloon	3.761553
17	buses	hot dog	buses	hotdog	114.507968	cat	dead	cat	dead	19.038447	trees	house	trees	house	13.234186	beach	dog	beach	dog	7.933236
18	love	buses\	love	buses	11.565985	dead	lecturer	dead	bicycle	6.287137	waterfall	jungle	waterfall	jungle	6.174657	bite	balloon	bite	balloon	14.035036
19	crash	buses	crash	buses	9.190353	time	dead	time	dead	7.836836	house	waterfall	house	waterfall	6.575992	bite	boat	bird	boat	8.318774
20	crash	cars	crash	park	20.812782	bomb	dead	bomb	dead	7.515918	panda	house	panda	house	6.685366	beach	balloon	beach	balloon	31.605261
21	buses	hotdog	buses	hotdog	27.942081	time	bomb	time	bomb	10.422355	jungle	house	jungle	house	14.943576	dog	balloon	dog	balloon	23.407149
22			library	hotdog	21.852969	time	dead	time	dead	25.978877	tree	jungle	trees	jungle	15.611541	ballon	bird	balloon	bird	9.393483
23	bus	crash	buses	crash	22.212071	lecturer	bomb	lecturer	bomb	10.653382	house	waterfall	house	waterfall	8.795837	balloon	bite	balloon	bite	15.761217
24	love	buses	love	buses	22.794715	dead	lecturer	dead	lecturer	6.881111	waterfall	house	waterfall	house	10.922339	dog	bite	dog	bite	11.075333
25	hotdog	love	hotdog	love	11.630034	cat	dead	cat	dead	5.568113	buses	burn	house	burn	16.104223	boat	balloon	bird	balloon	9.638042
26	park	hotdog	park	hotdog	14.652908	cat	bicycle	cat	bicycle	7.070439	house	panda	house	panda	11.09723	dog	beach	dog	beach	5.133132
27	hotdog	buses	hotdog	buses	28.310136	time	dead	time	dead	9.234337	waterfall	burn	waterfall	burn	13.181422	beach	bite	beach	bite	7.956653
28	park		park	crash	20.889361			time	dead	47.677454	panda	waterfall	panda	waterfall	7.387544	beach	balloon	bird	balloon	12.313167
29	hot	dog	crash	hotdog	16.371091	time	cat	time	dead	43.364729	jungle	panda	jungle	panda	9.735178	beach	dog	beach	dog	7.188307
30			hotdog	park	182.014337	bicycle	bomb	bicycle	bomb	28.562006	tree	house	trees	house	30.398264	balcany	boat	balloon	boat	55.711463
31	buses	hotdog	buses	hotdog	12.889318	bicycle	bomb	bicycle	bomb	13.952551	trees	house	trees	house	6.975736	bird	boat	bird	boat	6.860687
32	buses	library	buses	park	24.291963	dead	lecturer	dead	lecturer	12.551866	waterfall	jungle	waterfall	jungle	8.53463	balloon	beach	balloon	bird	28.290671

Figure A.5: Short-Term Memory Test Result Part 1.

A.14 Short-Term Memory Test Result Part 2

T5-A1	T5-A2	T5-C1	T5-C2	TIME	T6-A1	T6-A2	T6-C1	T6-C2	TIME	T7-A1	T7-A2	T7-C1	T7-C2	TIME	T8-A1	T8-A2	T8-C1	T8-C2	TIME
thunder	moon	thunder	moon	5.411664	hidden	bridges	hidden	bridges	4.962308	theif	car	thief	car	4.49389	smoke	road	smoke	road	6.596129
thunder	dolphin	thunder	dolphin	9.160004	basket	hidden	basket	hidden	10.153805	thief		thief	chip	14.37883	wife	smoke	wine	smoke	6.864029
dolphin	moon	dolphin	moon	7.641646	basket	cable	basket	cable	8.228545	chip	car	chip	car	9.114619	smoke	block	smoke	block	9.17944
strikes	thunder	strikes	thunder	10.18548	hidden	bridges	hidden	bridges	8.509521	train	chip	train	chip	8.533134	stage	block	stage	block	5.68036
moon	strikes	moon	strikes	8.566041	bridges	basket	bridges	basket	11.347691	train	book	train	book	7.84362	smoke	block	smoke	block	9.771299
plane	moon	plane	moon	9.09237		basket	hidden	basket	10.682666	car	train	car	train	17.957858	cook	stage	road	stage	9.796501
dolphin	storm	dolphin	storm	8.572699	cable	bridges	cable	hidden	22.898774	boat	chip	book	train	20.985209	wine	black	wine	block	10.771194
storm	thunder	plane	thunder	34.896362	basket	bridges	basket	hidden	24.68506	car	window	car	window	14.204553	wine	smoke	wine	smoke	13.228914
storm	dolphin	storm	dolphin	18.422936	hidden	basket	hidden	basket	9.020267	window	bush	window	book	15.483639	road	cook	road	cook	8.381683
storm	plane	storm	plane	17.92293	collapsed	bridges	camera	bridges	16.482418	car	window	car	window	8.193089	smoke	block	smoke	block	13.735687
moon		moon	strikes	12.3969	basket	collapse	basket	collapsed	10.033731	thief	train	thief	train	7.878487	road	cook	road	cook	7.034618
storm	stakes	storm	strikes	10.299343	bridges	camera	bridges	camera	4.672935	chip	thief	chip	thief	8.264504	wine	road	wine	road	4.537482
thunder	dolphin	thunder	dolphin	4.952784	cable	hidden	cable	hidden	5.847324	train	thief	train	thief	3.903487	stage	wine	stage	wine	4.138863
		thunder	strikes	5.030847			cable	collapsed	5.8055	window		window	car	5.829005	stage		stage	block	27.045268
moon	plane	moon	plane	10.168428	bridges	hidden	bridges	hidden	20.160129	chip	thief	chip	thief	11.406442	book	cook	block	cook	13.209981
strikes	moon	strikes	moon	4.796705	camera	cable	camera	cable	4.160837	book	train	book	train	4.489529	smoke	stage	smoke	stage	2.741422
dolphin	beach	dolphin	plane	60.816218	dogs	bridges	cable	bridges	40.061479	window	book	train	book	39.788745	cooke	smoke	block	smoke	18.624616
dolphin	moon	storm	moon	21.039234	basket	cable	basket	cable	6.479476	window	chip	window	chip	8.186274	cook	wine	cook	wine	5.749244
strikes	moon	strikes	moon	6.638941	camera	bridges	camera	bridges	6.958353	book	car	book	car	12.190004	block	stage	block	stage	11.154204
dolphin	thunder	dolphin	thunder	10.217818	camera	hidden	camera	hidden	11.243539	train	window	train	window	6.875209	wine	stage	wine	stage	7.128293
storm	strikes	storm	strikes	11.057361	crash	camera	cable	camera	20.159108	window	book	window	book	6.975698	stage	block	road	block	25.19586
thunder	storm	thunder	storm	7.758487	collapse	basket	collapsed	basket	9.659607	car	book	car	book	9.358086	smoke	block	smoke	block	8.344558
plane	strike	plane	strikes	13.629348	hidden	bridges	hidden	bridges	14.992756	chip	car	chip	car	10.715065	cook	smoke	road	smoke	14.936131
strikes	moon	strikes	moon	7.604565	bridges	camera	bridges	camera	7.835276	train	chip	train	chip	6.832305	road	wine	road	wine	6.292492
thunder	dolphin	thunder	dolphin	11.532208	cable	bridges	cable	bridges	7.940459	car	train	car	train	7.409419	cook	block	cook	block	8.434496
moon	strikes	moon	strikes	5.344422	collapsed	camera	collapsed	camera	8.069007	chip	train	chip	train	6.437209	smoke	block	smoke	block	5.423948
dolphin	thunder	dolphin	thunder	10.284477	camera	hidden	camera	hidden	9.632732	train	chip	train	chip	10.935725	smoke	stage	block	stage	10.251898
dolphin	strikes	dolphin	strikes	11.196869	cable	camera	cable	camera	7.410719	chip	tailor	chip	window	9.952449	block	road	block	road	7.124295
thunder	storm	thunder	storm	6.740379	camera	hidden	camera	hidden	6.985509	chip	window	chip	window	6.775961	smoke	stage	smoke	stage	6.635366
strike	storm	strikes	storm	10.09568	collapse	cable	collapsed	cable	21.622943	chip		chip	train	42.979732	stage	wine	stage	wine	41.559352
dolphin	strikes	dolphin	strikes	8.930648	basket	collapsed	basket	collapsed	7.81115	train	book	train	book	6.791911	car	block	road	block	10.419368
thunder	dolphin	thunder	dolphin	10.470404	bridges	hidden	bridges	hidden	14.930004	thief	chip	thief	chip	7.68022	road	cook	road	cook	8.168436

Figure A.6: Short-Term Memory Test Result Part 2.

A.15 Short-Term Memory Test Result Part 3

T9-A1	T9-A2	T9-C1	T9-C2	TIME	T10-A1	T10-A2	T10-C1	T10-C2	TIME
police	bomb	police	bomb	4.20255	shake	warm,	shark	worm	15.993917
belt	drink	belt	drink	14.346955	attacking	king	attacking	king	8.259541
smoke	bomb	smoke	bomb	9.692827	attacking	worm	attacking	worm	10.658239
police	smoke	drink	smoke	19.018013	shark	walk	shark	walk	7.917134
smoke	arrested	smoke	arrested	7.973705	strike	attacking	shark	attacking	12.352227
police		drink	bomb	25.253424	worm	king	worm	king	9.642871
belt	drink	belt	drink	12.702054	king	worm	king	worm	9.506507
arrested	belt	arrested	belt	13.797349	attacking	shark	attacking	shark	19.400234
police belt		police	belt	5.771756	walk	soap	walk	soap	9.164218
police	arrested	police	arrested	11.945924	work	slacking	walk	attacking	16.825254
belt	police	belt	police	21.130258		walk	king	walk	8.954801
police	drink	police	drink	5.659744	worm	attacking	worm	king	8.257336
belt	arrested	belt	arrested	4.404961	walk	worm	walk	worm	3.329609
police		police	smoke	5.434701	attacking		walk	attacking	10.712573
smoke	arrested	smoke	arrested	7.57489	king	walk	king	walk	14.159232
drink	arrested	drink	arrested	2.999697	soap	shark	soap	shark	3.838327
smoke		smoke	drink	69.347513	walk	worm	walk	worm	13.549564
smoke	bomb	smoke	bomb	2.889875	walk	attacking	walk	attacking	3.505203
belt	smoke	belt	drink	23.885617	king	soap	king	soap	7.198885
smoke	wine	smoke	drink	12.976887	attacking	worm	attacking	worm	8.768109
belt	arrested	belt	arrested	9.992364	shark	soap	shark	soap	6.368068
belt	police	belt	police	10.05346	worm	king	worm	king	6.360592
arrested	belt	arrested	belt	12.624134		attacking	worm	attacking	21.378213
police	drink	police	drink	8.093884	king	walk	king	walk	5.499433
police	drink	police	drink	7.090352	worm	king	worm	king	6.463808
police	smoke	police	smoke	3.765439	king	attacking	walk	attacking	16.015318
smoke	arrested	smoke	arrested	8.893056	storm	king	worm	king	7.941199
arrested	police	arrested	police	8.128705	worm	soap	worm	soap	10.166061
	smoke	drink	smoke	10.464198	worm	soap	worm	soap	9.142707
smoke	arrested	smoke	arrested	17.842996	shark	king	shark	king	24.304224
police	bomb	police	bomb	8.245477	work	worm	walk	worm	11.060749
police	smoke	belt	smoke	23.578618	shark	soap	shark	soap	8.281417

Figure A.7: Short-Term Memory Test Result Part 3.

A.16 Human-Robot Communication Explanatory Statements

Explanatory Statement to Participant

November 2015

Explanatory Statement – Group 1: Monash University Malaysia Residents

A Study of Human-Robot Conversation between a Human and a Robot Partner

This information sheet is for you to keep

・**Introduction of this Study:**

My name is Mr. Tang Tiong Yew, a PhD student at the School of Information Technology, Monash University Malaysia. This study is about developing new approaches to the way a companion robot interacts and communicates with humans. A companion robot is a robot that represents as a companion to a human user. Recent studies shows that frequent human-robot interactivity increase the engagement of education and teaching. Our robot companion is designed to have normal every day conversation with human user. As such, you may talk with the robot as you would another human, and you may talk with the robot about any subject that you would like.

・**Objective of the Study:**

One of the key objectives of the project is to develop a human-robot conversation system, which enables a natural conversation between humans and their robot partners in academic environment.

・**Benefit of the Study:**

The main purpose of this project is to stimulate your communication with a robot in an effort to improve education and teaching engagement in academic environment.

・**Notice:**

Participation is purely voluntary and no monetary payment will be made to you who are involved in this study. Furthermore, at your request, we will send you an electronic copy of the published outcomes of the study in the form of a PhD thesis.

・**How to return this questionnaire**

Please give the questionnaire to the person in charge that is on site.

・**What does the study involve?**

We are looking for twenty healthy individuals that are in Monash University Malaysia campus to participate in a data collection survey related to human-robot communication.

・**How much time will the study take?**

The study will require you to engage with a robot partner in conversation using English for 15 minutes and you will be asked to participate in two survey sessions taking around 10 minutes each.

・**The Study Data Gathering Process**

Upon completion of the consent form, you will have the opportunity to engage in conversation with our robot using the English language. The robot will start the first session by introducing itself to you and asking you some questions to get to know you, after these introductions you will then be free to converse with the robot. The human-robot conversation session will last 15 minutes, although you do not need to maintain the conversation for all of that time. You will be informed not to disclose any sensitive or individual identifiable personal information during the session. Any personal information will be anonymized. Video recordings of your human-robot interaction will be conducted but your face; individual identifiable conversation data or any individual identifiable data or any sensitive conversation data in the video recordings will be removed or blurred. These video recordings are for academic study purposes only and they will be managed with secure access protection. Finally, you will be asked to complete two similar questionnaire survey forms about your conversation experiences with the robot-partner. The two survey sessions will be conducted at the before your first conversation with the robot, and again after conversation session.

・**Can I Withdraw from this Study?**

This is entirely voluntary based and you are under no obligation to consent to participation. You can withdraw at any point during the study process.

・**Confidentiality**

Your individual identifiable conversation data or any individual identifiable data or any sensitive conversation data in the video recordings will be removed or blurred. You will not have any physical contact with the robot partner but just verbal communication with it.

・**Storage of Data**

The storage of the data collected will comply with the University regulations. A report of the study may be submitted for thesis publication, but you will not be identifiable in such a report.

- **Result**

If you would like to be informed about the study's findings, please contact Mr. Tang Tiong Yew on [redacted]

- **You have all the rights to stop your participation in this study at any time**

If you feel uncomfortable at any point, during the study questions, or during your conversation with our robot, then please stop your participation immediately. However, our study and data collection process has been designed to be as neutral as possible.

If you would like to contact the person in charge about any aspect of this study, please contact the Student Investigator:	If you have a complaint concerning the manner in which this study is being conducted, please contact:
Mr. Tang Tiong Yew Room 2-4-18, School of Information Technology Monash University Malaysia [redacted] Supervised by: Dr. Simon Egerton [redacted]	Mr Chua Khong Wai Senior Manager, Research Management Monash Sunway Campus Jalan Lagoon Selatan 46150 Bandar Sunway Selangor Darul Ehsan, Malaysia [redacted]

Consent Form for Participants

November 2015

Explanatory Statement – Group 1: Monash University Malaysia Residents

Human-Robot Communications with a Robot Partner

Note: This consent form will remain with Monash researcher for their record keeping

I agree to take part in the Monash University study specified as above. I understand the project explained to me, and I have read the Explanatory Statement, which I keep for my records. I understand that agreeing to take part means that:

I agree to fill in two survey forms (before and after) about my chatting experiences with a robot.
I agree to have a non-identifiable video recording (15 minutes session) only during my chatting session with a robot.
I understand that these non-identifiable video recordings are for academic study purposes only and they will be managed with security access protection.

I understand that my participation is voluntary, that I can choose not to participate in part or all of the project, and that I can withdraw from the research at any point, without being penalised or disadvantaged in any way. I understand that any data that the researcher collects for use in reports or published findings will not, under any circumstances, contain names or identifying characteristics. I understand that none of your identifiable information will be collected. Data collected from this research may be published online for research purpose only.

I had understood all the terms in this consent form and I agree to them.
☐ Yes ☐ No

Participant's Name:

Participant's Signature:___________________________________ Date:________________

A.17 Human-Robot Communication Questionnaire

Participant ID:

A Study of Human-Robot Conversation between a Human and a Robot Partner

Before human-robot conversation:

- **Section 1**
- **Section 2**
- **Section 3**

After human-robot conversation:

- **Section 4**
- **Section 5**
- **Section 6**

Participant ID:

Section 1: Demographic Data

This section is to capture the participant's demographic data in the test population.

1. Which age range are you in? (Please answer one correct answer from the options)

□ 18～20 □ 20～30

□ 30～40 □ 40～50

□ 50～60 □ Above 60

2. What is your gender? (Please answer one correct answer from the options)

□ Male □ Female

3. Which school you are in? (Please answer one correct answer from the options)

□ Information Technology □ Social Science and Arts

□ Medicine and Health Sciences □ Engineering

□ Business □ Pharmacy

□ Monash Staff □ Other ______________________

Section 2: State-Trait Anxiety Inventory (STAI)

This section is to capture the participant's current stress emotional state (reference[1]).

No	STAI Questions	Very Much	Moderately	Some what	Not at all
1.	I feel calm.				
2.	I am tense.				
3.	I feel upset.				
4.	I am relaxed.				
5.	I feel content.				
6.	I am worried.				

NOTES:

[1] "The Development of a Six-Item Short-Form of the State Scale of the Spielberger State-Trait Anxiety Inventory (STAI)", Theresa M. Marteau, Hilary L Bekker, British Journal of Clinical Psychology, 1992 http://www.researchgate.net/publication/21762872_The_Development_of_a_Six-Item_Short-Form_of_the_State_Scale_of_the_Spielberger_State-Trait_Anxiety_Inventory_%28STAI%29

Participant ID:

Section 3: Negative Attitude Towards Robots Scale (NARS)

This section is to capture the participant's perceptions and attitude towards robot (reference[2]).

No	NARS Questions	Strongly agree	Slightly agree	Feel exactly neutral	Slightly disagree	Strongly disagree
1.	I would feel uneasy if robots really had emotions.					
2.	Something bad might happen if robots developed into living beings.					
3.	I would feel relaxed talking with robots.					
4.	I would feel uneasy if I was given a job where I had to use robots.					
5.	If robots had emotions, I would be able to make friends with them.					
6.	I fell comforted being with robots that have emotions.					
7.	The word "robot" means nothing to me.					
8.	I would feel nervous operating a robot in front of other people.					
9.	I would hate the idea that robots or artificial intelligences were making judgments about things.					
10.	I would feel very nervous just standing in front of a robot.					
11.	I feel that if I depend on robots too much, something bad might happen.					
12.	I would feel paranoid talking with a robot.					
13.	I am concerned that robots would have a bad influence on children.					
14.	I feel that in the future society will be dominated by robots.					

15.	What do robots remind you of?	□ Human □ Animal □ Machine
16.	Where will robots be used?	□ Home □ Office □ Schools □ Hospitals □ Factories □ Hazardous Location (contaminated areas, battlefields, etc.) □ Remote Locations (deep sea, space, etc.)
17.	Did you ever play with a robot before?	□Yes □ No

2 "The influence of people's culture and prior experiences with Aibo on their attitude towards robots", Christoph Bartneck et. al., AI & Soc (2007)

Participant ID:

Section 4: Related Questions for Robot Conversation

This section is to capture specific participant's experiences regarding to human-robot conversation in this study.

No	Questions	Strongly agree	Agree	Neutral	Disagree	Strongly disagree
1.	I have much good companionship from my family and friends.					
2.	I like new technologies such as smart phone, tech gadgets, tablets, robot and computers.					
3.	I think the robot pays attention to me quickly.					
4.	I feel like the robot is aware of its environment.					
5.	I think the robot expressed many of its thoughts.					
6.	I think the robot have many creative ideas.					
7.	I think the robot conversation topic is relevant to certain degree of the information available in our current situation.					
8.	I think I will tell others about my experiences with the robot.					
9.	I feel that the robot can keep my mind alert.					
10.	I think I will remember the robot after this study.					
11.	I think the robot companionship can make me feel happy.					
12.	I think the robot can be my companion robot.					
13.	What did you enjoy the most about your time with the robot?					
14.	What did you enjoy the least?					
15.	If you could improve something about the robot, what would it be?					

Participant ID:

Section 5: State-Trait Anxiety Inventory (STAI)

This section is to capture the participant's current stress emotional state.

No	STAI Questions	Very Much	Moderately	Some what	Not at all
1.	I feel calm.				
2.	I am tense.				
3.	I feel upset.				
4.	I am relaxed.				
5.	I feel content.				
6.	I am worried.				

NOTES:

Participant ID:

Section 6: Negative Attitude Towards Robots Scale (NARS)

This section is to capture the participant's perceptions and attitude towards robot

No	**NARS Questions**	**Strongly agree**	**Slightly agree**	**Feel exactly neutral**	**Slightly disagree**	**Strongly disagree**
1.	I would feel uneasy if robots really had emotions.					
2.	Something bad might happen if robots developed into living beings.					
3.	I would feel relaxed talking with robots.					
4.	I would feel uneasy if I was given a job where I had to use robots.					
5.	If robots had emotions, I would be able to make friends with them.					
6.	I fell comforted being with robots that have emotions.					
7.	The word "robot" means nothing to me.					
8.	I would feel nervous operating a robot in front of other people.					
9.	I would hate the idea that robots or artificial intelligences were making judgments about things.					
10.	I would feel very nervous just standing in front of a robot.					
11.	I feel that if I depend on robots too much, something bad might happen.					
12.	I would feel paranoid talking with a robot.					
13.	I am concerned that robots would have a bad influence on children.					
14.	I feel that in the future society will be dominated by robots.					

15.	What do robots remind you of?	□ Human □ Animal □ Machine
16.	Where will robots be used?	□ Home □ Office □ Schools □ Hospitals □ Factories □ Hazardous Location (contaminated areas, battlefields, etc.) □ Remote Locations (deep sea, space, etc.)
17.	Did you ever play with a robot before?	□Yes □ No

A.18 Human-Robot Communication Questionnaire Result

A.19 Human-Robot Communication Questionnaire Result Part 1

No	S1-1	S1-2	S1-3	S2-1	S2-2	S2-3	S2-4	S2-5	S2-6	S3-1	S3-2	S3-3	S3-4	S3-5	S3-6	S3-7	S3-8	S3-9	S3-10	S3-11	S3-12	S3-13	S3-14	S3-15	S3-16	S3-17	S4-1	S4-2	S4-3	S4-4	S4-5	S4-6	S4-7	S4-8	S4-9	S4-10	S4-11	S4-12
1	3	1	1	1	4	4	1	1	4	5	2	1	2	2	3	4	4	4	5	2	4	2	2	3	2,3,4,5,6,7	1	1	1	2	2	2	2	2	2	3	3	3	3
2	3	2	1	3	3	4	3	3	4	5	4	2	2	1	2	5	5	4	5	4	4	5	2	3	4,5,6,7	2	3	2	3	2	3	3	2	1	3	1	1	2
3	3	2	1	3	2	4	3	1	4	1	1	5	5	5	5	5	3	5	5	1	1	1	1	3	4,5,6,7	1	1	5	4	4	3	3	3	1	5	1	5	5
4	3	2	4	1	4	4	1	1	4	1	1	1	5	2	2	5	5	5	5	2	5	3	2	3	1,2,3,4,5,6,7	2	1	2	2	1	2	2	2	1	2	1	2	2
5	3	1	4	2	4	4	2	2	2	3	2	2	4	3	2	4	3	2	4	3	4	4	1	3	4,5,6,7	1	2	2	2	4	1	1	2	2	2	2	2	2
6	3	2	1	1	4	4	1	2	4	4	5	3	4	2	2	5	3	4	4	4	3	4	5	3	2,3,5,6	2	2	3	3	4	4	4	2	2	3	2	4	4
7	2	1	1	2	2	4	3	3	2	2	3	3	3	3	4	3	3	2	3	2	2	3	2	3	5,6,7	1	2	1	2	4	3	4	2	2	3	3	3	2
8	1	1	1	1	4	4	1	1	4	3	2	1	5	3	2	5	5	5	5	2	5	5	3	3	3,5,6,7	2	1	1	3	2	2	2	2	2	3	2	4	5
9	5	1	1	1	4	4	2	2	4	1	1	3	3	2	4	4	4	3	4	2	5	2	3	3	1,2,5,6	2	1	3	2	3	2	3	2	1	1	1	1	2
10	4	2	1	1	4	4	1	2	4	5	5	3	5	1	1	3	2	5	5	4	5	3	5	3	1,2,5,6,7	2	1	1	3	4	2	3	2	2	3	2	2	3
11	3	1	1	3	2	4	3	3	4	4	2	2	4	3	3	4	4	4	4	2	3	2	2	3	1,2,3,4,5,6,7	2	1	1	2	2	2	3	2	1	2	2	2	2
12	4	2	1	1	4	4	1	1	4	4	3	2	5	2	3	4	5	4	5	3	5	3	2	3	1,2,3,4,5,6,7	2	1	1	2	4	4	4	4	2	3	2	3	3
13	2	2	5	2	3	4	2	2	3	2	2	3	3	3	3	4	1	3	3	2	4	2	2	3	5,6,7	2	2	2	2	3	2	2	2	2	2	2	3	3
14	3	1	5	1	2	2	2	1	2	4	3	4	4	4	4	4	4	4	4	4	4	4	4	1	2,7	2	1	1	1	2	2	2	2	2	2	2	2	2
15	2	1	1	1	3	4	2	2	3	2	3	2	4	3	2	4	3	4	5	3	3	4	5	3	2,5,6,7	2	1	2	1	1	1	1	2	1	1	1	1	1
16	2	1	5	1	4	4	1	1	4	2	3	1	5	2	2	5	4	2	4	2	4	4	2	3	1,2,3,4,5,6,7	2	1	1	2	3	3	4	2	1	3	2	2	2
17	3	2	4	1	4	3	1	1	4	5	5	1	2	2	2	5	2	3	5	3	5	4	5	3	2,4,5,7	1	1	2	2	3	4	3	2	2	4	2	4	3
18	2	1	5	1	4	4	1	1	4	5	4	2	4	2	2	3	3	4	4	4	4	4	3	3	1,4,5	1	2	1	4	4	4	3	3	1	1	1	2	2
19	2	1	5	1	4	4	2	4	4	2	3	2	4	2	4	5	5	2	5	2	4	5	1	3	1,2,3,4,5,7	1	1	1	3	4	2	4	2	1	2	1	4	2
20	2	2	5	2	4	4	3	2	2	5	1	3	2	2	3	3	4	2	3	3	3	2	2	3	15,6	2	3	2	3	3	2	2	2	1	2	2	2	2
21	1	2	1	2	3	4	3	3	4	4	3	3	3	3	3	4	2	4	3	2	3	3	2	3	5,6,7	1	2	2	3	4	3	3	1	2	3	2	3	3
22	2	1	1	1	4	4	3	2	4	2	2	3	4	3	3	4	4	2	5	1	2	4	2	3	1,4,5,6,7	1	2	1	2	3	2	4	2	2	3	1	3	4
23	2	2	1	2	4	4	2	2	4	5	3	3	3	2	2	4	1	3	5	2	5	5	3	3	5,6,7	2	2	1	2	2	3	2	2	2	2	2	2	2
24	2	2	1	2	3	4	4	4	3	3	3	3	4	3	3	2	3	3	4	3	4	3	2	1	1,2,3,4,5,6,7	1	1	1	3	3	3	3	2	2	3	3	4	4
25	5	1	1	1	4	4	2	1	4	3	4	2	5	2	2	5	5	4	5	3	5	5	3	3	1,2,3,4,5,6,7	2	3	1	4	3	2	3	3	1	2	1	3	3
26	3	1	1	1	4	4	1	1	4	3	3	2	3	3	5	5	5	3	3	3	3	3	1	3	7	2	4	1	2	2	3	3	2	3	3	3	3	4
27	2	1	1	2	2	4	2	2	4	5	5	4	4	3	3	3	2	3	4	3	2	5	2	3	1,2,3	2	2	1	2	2	2	2	2	1	2	2	2	2
28	1	1	1	2	3	4	3	2	4	2	2	1	5	3	3	4	2	4	3	2	4	4	1	3	2,3,4,5,6,7	2	2	1	2	2	1	3	3	2	1	1	2	2
29	1	1	1	1	3	4	1	1	3	4	2	2	5	2	3	5	5	4	5	2	4	5	1	3	1,2,3,4,5,6,7	1	1	1	2	2	2	1	2	1	2	2	2	3
30	2	2	5	3	3	4	2	2	2	4	4	2	3	3	3	4	3	3	3	3	1	4	4	3	4,5,6,7	2	2	2	3	2	2	3	2	2	3	2	3	2

Figure A.8: Human-Robot Communication Questionnaire Result Part 1.

A.20 Human-Robot Communication Questionnaire Result Part 2

S4-13	S4-14	S4-15
Answering some intelliget question. E.g. Can you destroy yourself?	Late response to questions, wrong answer, not knowing when to start asking question	The three points above
talking with robot was very interesting	I had to repeat some questions and robot was not able to answer	the level of intelligence
It was able to hold a conversation to a certain level	Having to repeat myself, the conversation was unmature and lacked flow	The accuracy of response from the robot
When Jimmy understand what I asked	Try to understand what Jimmy said	Different language
Almost seamless conversation	Some conversation were put on hold and resummed sometime late	Answering in listening and to continue a conversation topic
Answering with funny statements	when the conversation can't evolve	can make jokes
It can understand, interpret human communication	It is had for the robot to understand us (human)	It's understanding capability
It knew human activities such as playing football and wathing movies	It kinda got stuck in on infinite loop at the end	Maybe the robot could do more activities.
Intelligent, friendly robot.	Low volume, not loud enough, sometimes not audible.	More humanized voice.
She can understand my question and give me feedback	The mechanical sound a bit distracting	Make the movement more human like and more human cute essen/habit in speaking
The overall conversation and its body language		Audio shold be improved, move body lanuage and eye movement, stand & walk while talking
It was my first experience interacting with a robot that itself was special	I could not understand the few replies from robot. Our timing was off. It wasn't free flowing conversation.	The timing. Synchronization when I say something, it should reply when I stop. It starts in between.
Taking to robot (i.e. having conversation)	Have to think of questions	Maybe reply spontaenously
The robot can reply my questions	Take time for the robot to respond	Enhance interactive with the user
I think the robot is funny	maybe the robot can response faster	I think could be the speech recognition speed.
Its voice friendly & cute	limited answer	physical movements
It shape and size made it so cute	when it talked irrelevant	made it more alert
Interesting, but rather random questions.	Response is limited at the moment	Contextualising based on the subject, but it is not easy as I understand
Very cleaver and responsive, has a friendly character.	Timing is slow but understandable. Can't pick up my 'asian' accent	Different languages. Emotion capabilities.
His thought were similar to mine! Mean pretty inclined to what I think	I liked it!	the way he percense things, It clearer understanding is needed. Pronouciation.
it being a cheeky robot	not answering my questions, but I am alright with it.	
It is cute & seems nice & mama know about you	A litte creepy of times, and too constant eye contact	Understanding & speed
about its humours and the way it outsmarts you. Its reaction and gestures.	N/A	I wish it would move around, you know like walk or dance. More interaction.
Random chat on different topics	Slower reaction time & technology barriers	none
One never knows what the robot is about to say	The robot is sometimes too slow	The robot is sometimes too slow
The new technology that emerged	talks very fast sometimes & don't let me to talk	good listening would behelpful. When my lips are moving shouldn't interrupt :)
Chatting		the questioning time
The robot like to express its thoughts	Well, for some reason it keeps asking me why am I lying? ^_^	Better control of expressions emotions and thoughts
Its ability to answer specific questions	Its creepy robot voice	Improve robot's voice, make it friendlier
The way the robot asked questions when I didn't know what to ask.	Awkward silence	Detect pronouciation better

Figure A.9: Human-Robot Communication Questionnaire Result Part 2.

A.21 Human-Robot Communication Questionnaire Result Part 3

S5-1	S5-2	S5-3	S5-4	S5-5	S5-6	S6-1	S6-2	S6-3	S6-4	S6-5	S6-6	S6-7	S6-8	S6-9	S6-10	S6-11	S6-12	S6-13	S6-14	S6-15	S6-16	S6-17
1	4	3	1	2	4	4	2	2	2	2	3	5	2	4	5	2	5	2	2	3	2,3,4,5,6,7	1
3	4	4	3	2	3	5	4	2	4	2	2	5	4	4	5	4	5	4	2	1	1,5,6,7	2
3	4	4	3	1	4	1	1	5	3	5	5	5	3	5	5	1	1	1	1	3	4,5,6,7	1
1	4	4	1	1	4	2	1	1	5	2	4	5	5	5	5	2	5	5	2	3	1,2,3,4,5,6,7	1
1	4	4	2	2	4	3	2	2	4	2	2	4	4	2	4	3	4	3	1	3	4,5,6,7	1
1	4	4	3	3	4	3	4	2	4	3	2	4	3	4	4	4	4	4	4	3	1,2,3,6,7	1
2	2	3	2	2	3	2	2	3	3	3	4	3	3	1	3	2	3	3	2	3	5,6,7	1
1	4	4	1	2	4	4	4	2	5	3	2	5	4	4	4	1	4	5	3	1,3	3,5,6	1
1	4	4	1	1	4	2	3	2	3	2	3	4	4	3	5	3	5	2	3	3	1,2,3,5,6,7	2
1	4	4	1	2	4	5	3	2	5	1	1	3	5	5	5	2	5	5	3	1	1,2,3,4,5,6,7	1
2	3	4	2	2	4	5	2	2	4	3	2	4	5	5	4	2	4	2	2	1,3	1,2,3,4,5,6,7	2
1	4	4	1	1	4	5	5	3	5	3	3	4	5	5	5	5	5	5	2	3	1,2,3,4,5,6,7	1
3	1	4	3	3	3	2	2	4	2	3	4	4	2	3	2	2	1	2	2	3	5,6,7	1
2	2	4	2	2	4	2	2	2	2	2	2	4	2	2	4	4	4	4	4	3	1	1
1	2	4	3	2	4	3	4	1	4	2	3	5	4	4	3	4	4	4	4	3	2,5,6	1
1	4	4	1	1	4	4	4	2	5	2	1	5	5	5	5	4	5	2	1	1,3	1,2,3,4,5,6,7	1
1	4	4	2	1	4	4	4	3	2	2	2	3	2	4	3	4	4	4	3	3	2,5,7	1
2	2	2	1	1	2	3	3	3	3	2	2	3	2	3	4	3	3	5	2	3	1,3,4,5,7	1
1	4	4	1	3	4	3	4	1	5	1	3	5	5	3	5	4	5	5	3	3	1,2,3,4,5,7	1
2	2	2	2	1	2	2	3	2	4	2	3	3	4	3	3	3	4	2	3	3	1,5,6	1
1	3	4	1	2	4	3	2	3	4	3	3	4	3	3	3	2	5	3	2	3	5,6,7	1
2	3	4	3	2	4	2	2	4	3	3	4	4	4	2	2	2	2	3	2	3	4,5,6,7	1
1	4	4	1	3	4	4	3	4	4	2	2	5	4	4	5	4	4	3	2	1	2,3,5,6,7	1
3	3	4	4	4	4	3	3	4	3	4	4	2	3	4	4	2	4	3	2	3	1,2,3,4,5,6,7	1
2	2	4	3	1	4	4	4	3	5	2	2	5	4	4	5	4	4	5	3	3	1,2,3,4,5,6,7	1
1	4	4	1	1	4	5	3	3	3	3	2	5	3	3	5	2	3	3	1	3	1,2,7	2
2	3	4	2	2	3	4	4	3	4	2	2	4	2	3	4	4	4	4	2	3	1,2,3,5,7	2
1	4	4	1	2	4	4	3	1	5	2	2	4	4	4	4	3	4	4	2	1,3	1,2,3,4,5,6,7	1
1	3	4	1	1	4	2	2	3	4	2	2	5	5	4	4	1	4	5	1	3	1,2,3,4,5,6,7	1
2	3	4	2	2	3	4	4	4	4	1	2	5	4	4	4	4	4	4	4	3	1,2,3,4,5,6,7	1

Figure A.10: Human-Robot Communication Questionnaire Result Part 3.

A.22 iPhonoid Robot Partner Hardware Configurations

The iPhonoid robot partner system was initially developed by Woo et al. [184]. The following figures illustrate the robot partner hardware experiment setup in the proposed AICO framework in this research used in Chapters 5.

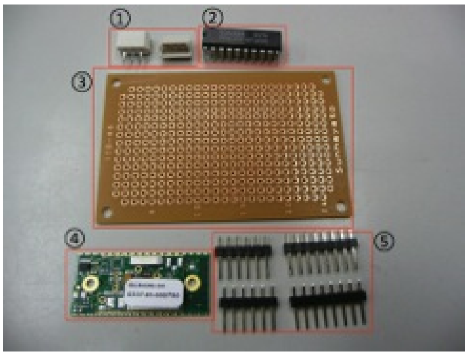

Figure A.11: The building components for developing the Arduino shield: 1. Molex 5267-03A-X 2.5mm Pitch 5267 Series Board connector straight 03P. 2. TOSHIBA 74HC241AP. 3. Universal board. 4. Bluetooth module OLS426i. 5. Pin socket (female) 1 X 6 (two), 1 X 8 (two)

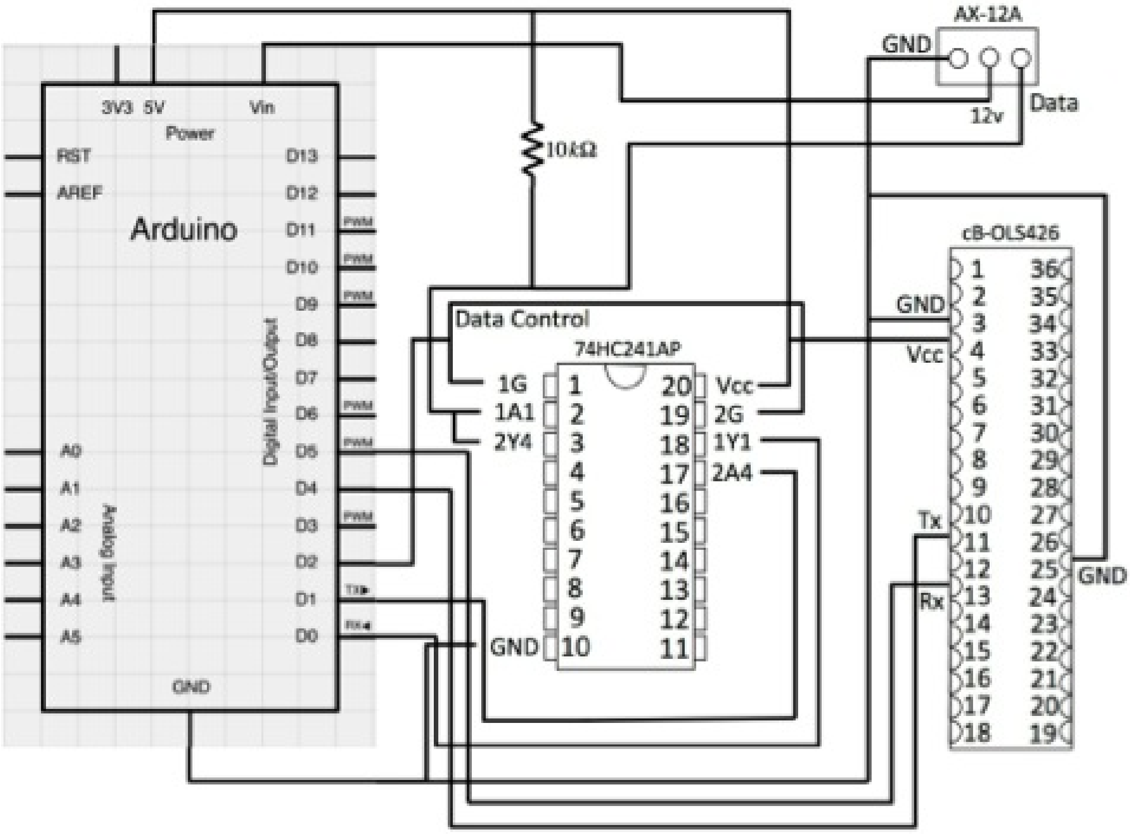

Figure A.12: Circuit Board Blueprint of Arduino and its shield.

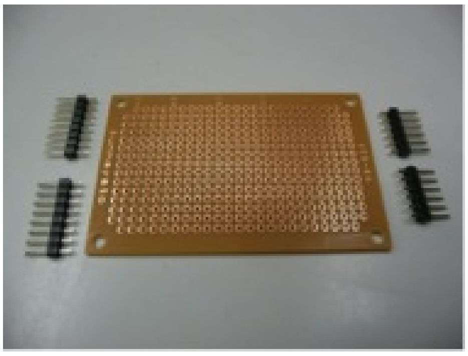

Figure A.13: The pin socket and universal board.

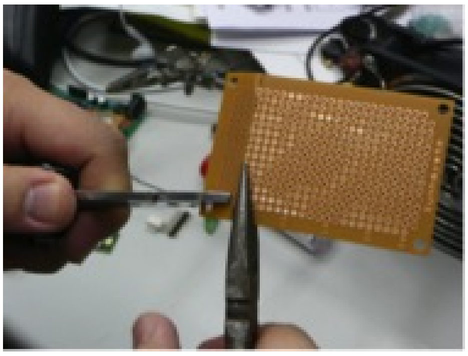

Figure A.14: Reducing the universal board size to fit the Arduino board by cutting it.

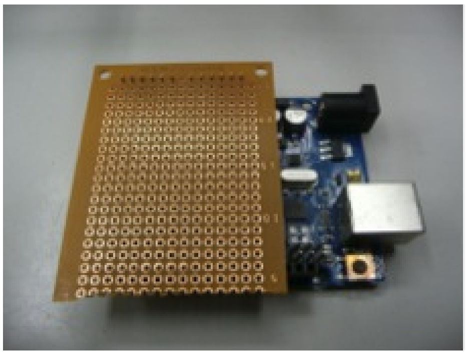

Figure A.15: Preparing the soldering pin socket to the universal board as Arduino shield.

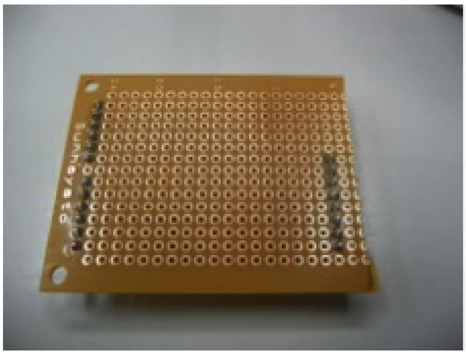

Figure A.16: Soldering of pin sockets to the universal board.

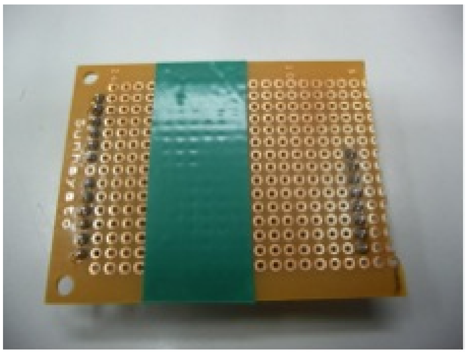

Figure A.17: The insulation tape for electronic insulation between the Bluetooth module OLS426i and the universal board.

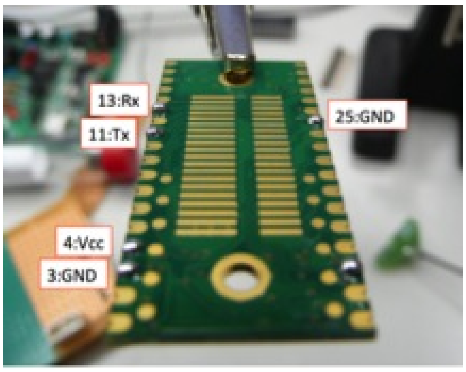

Figure A.18: Soldering on the Bluetooth module to the universal board.

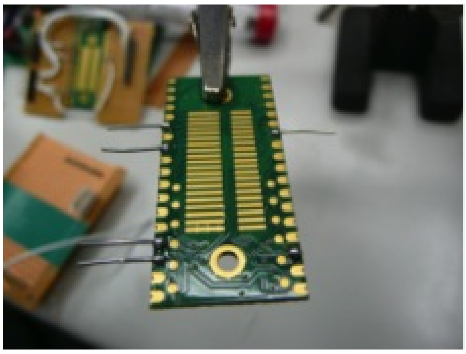

Figure A.19: Soldering the wire to the Bluetooth board with a length of about 2 cm.

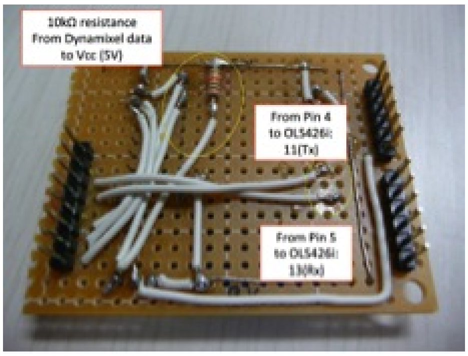

Figure A.20: Soldering the wires to the universal board accordingly.

Figure A.21: Finished soldered shield board.