The Simulation of Action Strategies of Different Personalities

In Perspective of the Interaction between Emotions, Motivations and Cognition

(An Experimental Study in the Field of Cognitive Psychology and Artificial Intelligence)

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Chapter

1

Introduction

1.1 Introduction:

Artificial intelligence is a branch of science associated with logic, psychology, dynamic system, philosophy, linguistics and computer science. It has also many important links with other fields. The ability to combine knowledge from all these fields will benefit a progress in the quest of creating an intelligent entity. Currently, artificial intelligence rather seems to concentrate itself on more inventive applications. However, towards enhancing these applications, more human features are needed to artificial intelligent agents and robotics (i.e., human emotions and action regulation).

Moreover, agent technology is a fast growing area of research in artificial intelligence. Intelligent agents are simply defined as the autonomous problem-solving entities residing in an environment to solve problems. They automatically execute intelligent task by adaptation to changes in their environment and interaction with other agents. This technology is expected to become the next generation of software. In addition, robots and intelligent agents will soon be a part of our everyday lives. In general, it means that we can expect that robots and intelligent agents will act and react in many ways that a human can. According to Bradshaw (1997, p.3), the more intelligent the robot, the more capable of pursuing its own self-interest rather than its master's. The more humanlike the robot, the more likely to exhibit human frailties and eccentricities.

1.2 Dörnerians' Approach:

Cognitive Psychology considers psychic processes (i.e., thinking, learning and memory) as processes of information processing. There are a lot of theoretical systems which describe human thought as information processing. But how could one describe motivation and emotion in terms of information processing? Dörnerians' approach can respond to such question because "Dörnerians" are interested in action regulation of man. Dörner and his co-workers developed PSI-theory that explained human action regulation in perspective of the interaction between emotions, motivations and cognition. In this theory, man is a motivated emotional-cognitive system, not only a cognitive system in the sense of contemporary cognitive science. Bartl and Dörner (1998, p.1) noted that a single theory of cognitive processes does not succeed in explaining human behaviour.

Furthermore, it is necessary to include assumptions about the dynamics of emotions and motivations. Computer programs were constructed to simulate the theoretical assumptions of PSI-theory (see: Dörner & Hille, 1995; Hille, 1997; Schaub, 1997). The PSI-theory is formulated completely in terms of the theory of neuronal networks (Bartl & Dörner, 1998, pp.1-2).

To understand the human ability to cope with complex and unknown realities, it is not only necessary to explore the cognitive system of man but also to investigate additionally the relationships between cognition, emotion, and motivation (see: Dörner & Hille, 1995, p.3828). Dörner's theory describes the informational structure of an intelligent, motivated, emotional agent (PSI) which is able to survive in arbitrary domains of reality. This agent has different motives (i.e. need for energy, water, pain-avoidance, certainty and competence). The cognitive processes of this agent are modulated by emotional states and high mental processes (i.e. memory, planning, and thinking). The hypotheses of the theory are presented in mathematical form. It is shown that the theory enables the simulation of different forms of emotional behaviour found with subjects. (Dörner, 2003, p. 75).

1.3 Research Motivation:

Computers are able to play chess, they are even much better in it than most people. Computers are also able to control a power plant. They are more reliable than man. However, one cannot expect from them either to make suggestions for improvement. They will never look for a better way to do their job than the programmed one. They will never change their program automatically in case of a sudden change of the environment. Artificial intelligence suffers from certain shortcomings. Furthermore, the systems of artificial intelligence are rigid and domain specific. They are not able to adapt their behaviour to the conditions of the current situation (Dörner & Hille, 1995, p.3828). We are particularly interested in how the artificial robot performs with respect to the human character. We model human thinking, as an example for a mental process, on a computer and see if our theory is correct (ibid). We believe that the robot's behaviour or performance will lead to a high achievement like human. Thus, this research takes a closer look to apply PSI-theory to simulate different characters. For this purpose, an experiment was constructed followed by simulating the experiment's results. This research is situated within a larger project with the ultimate goal of developing an intelligent robot that exhibits and simulates high mental cognitive processes and interacts socially and verbally like human manner.

1.4 Research Domain:

Wagman (1993, p.1) argued that the augmentation of intelligence in computers may be achieved by two general methods or a combination of methods. In the first general method, the computer models the cognitive processes of human intellect. Augmentation of computer intelligence through this method requires the continuous expansion of reliable and valid knowledge concerning human cognitive processes. In the second general method, the intelligence of the computer models formal logical structures and processes. Augmentation of computer intelligence through this method requires the continuous expansion of reliable and valid knowledge concerning the theory and application of systems of logic and coordinated sets of programming languages.

Computer games offer interesting and challenging environments for many, more isolated, research problems in artificial intelligence (Laird & van Lent, 2000, p.1178). For example, placing agents into a game environment offers interesting and challenging environments for research problems in artificial intelligence. This study was designed and carried out to contribute towards our vision of the future of simulating cognitive processes.

1.5 Research Questions and Hypotheses:

The main purposes of the current dissertation are to determine whether PSI-agent (and of course the theory behind the agent) can simulate different strategies in an uncertain complex problem environment that has multi-goals and can PSI-agent simulate single cases. For that aims we used the scenario island-game to compare the behaviour of PSI with the behaviour of experimental subjects. We assume that human participants in our experiment are subject to certain cognitive and motivational processes. The current research will attempt to answer and to investigate the following questions and hypotheses:

Questions and Hypotheses
▪ **What is the state of PSI-agent's behaviour in corresponding to agent criteria?**
▪ **Can PSI-agent simulate all the different action strategies that can be found with man?**
▪ **It is possible to simulate the behaviour of individual human beings by PSI-agent.**
▪ **How can we improve the PSI-agent respectively to the theory behind the agent?**

Table 1.1: Questions and hypotheses.

The method used to resolve the questions of this research consists of both psychological experiment and computer simulation that simulate the different action strategies found in the experiment by using PSI-agent. The method that used to analyze the results of the experiment is based on both qualitative and quantitative analyzation of the participants' behaviour in island-game.

To investigate our questions and hypotheses, we will do the following steps: Firstly, we will give an overview about the architecture of the PSI-theory and the underlying theoretical assumptions. Secondly, we will describe the scenario "island–game" and the experimental design. Thirdly results of the experiment will be discussed and explained in perspective of concepts of the PSI-theory. Fourthly, we will simulate subjects' strategies and two single cases by PSI-agent. Finally we will discuss results of the simulation and give some hints towards improving and elaborating the PSI model of action regulation.

1.6 Organization of the Dissertation:

The dissertation consists of six chapters and the literature is organized in a hierarchy structure. We will first present the framework of artificial intelligence and simulation environment and then identify agent components to highlight the desired features in agent architectures for the tasks and environments. Next, we will present PSI-theory as an example of intelligent architecture that is used to simulate human motivations, emotions and cognitive processes (see figure 1.1). Method, simulation, results and discussion chapters are organized in a hierarchy structure too. These chapters are organized as the following:

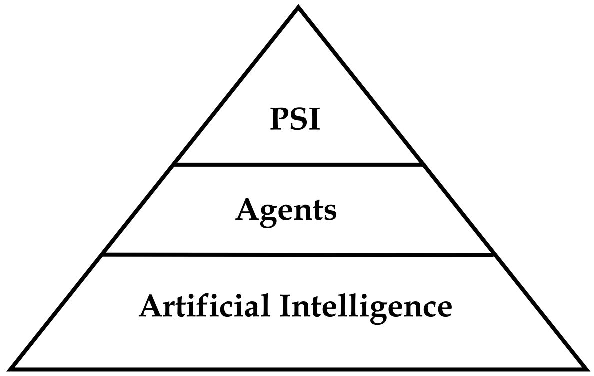

Figure 1.1:
Organization of Literature.

Chapter One:

Chapter one has been an introductory chapter. It has introduced the main problem area that the dissertation addresses and a background to the work in the dissertation. Research motivation, domain and research questions have been also demonstrated.

Chapter Two:

Chapter Two will present an overview of the framework of artificial intelligence and simulation. It will provide a more detailed discussion of various aspects and definitions of the artificial intelligence field. Moreover, goals, basic terminology, characteristics, advantages, benefits and applications of the field will be discussed. Neural networks and expert systems will be reviewed. Finally, we will describe the field of simulation together with types of simulations and simulation environments.

Chapter Three:

Chapter Three presents approaches for agent design and specifies which basic components and features must be present in an agent generally and cognitive agent especially. It will also outline the characteristics and difficulties face agents, and the types of agents. Finally, this chapter states the desirable properties and criteria that an intelligent system or agent must have.

Chapter Four:

Chapter four gives a review of PSI's architecture and the underlying philosophy behind the architecture that is the basis for the later chapters in the dissertation, presenting its several aspects, its various components, implementations and problem domain that PSI's architecture is designed for it. Moreover, related work and description of PSI's action and behaviour is also reviewed.

Chapter Five:

Chapter five describes the experimental set-up, materials, apparatus, instructions and experimental design and procedure. Furthermore, results of the experiment and procedures that were used to analyze subjects' strategies during the experiment will be explained.

Chapter Six:

The intention of this chapter is to see if we have achieved our goals of simulating different strategies. Thus, chapter six gets to the central questions of the dissertation, shows both the simulation of different strategies that had found and the simulation of two different single cases. Moreover, an evaluation for PSI's agent determined by agent criteria to estimate PSI's action and behaviour is also reviewed. Discussion, suggestions, argumentations, work in progress, future work and contributions to PSI theory and research will be also shown to see if the ideas worked and where can things be improved. Such data could provide a consequential contribution to enhance and develop our PSI-theory.

Chapter

2

Artificial Intelligence & Simulation

Summary

This chapter provides an overview of the framework of artificial intelligence. In section 2.1, we will provide a general description and definition of the artificial intelligence field. As well, goals and applications of the field will be demonstrated. Finally, basic artificial intelligence terminology such as Schemata, Algorithms and heuristics will be shown. In section 2.2, description, definitions, characteristics, advantages, benefits and applications of expert systems will be discussed. Neural networks and connectionist framework will be reviewed in section 2.3. Moreover, fundamentals and characteristics of connectionist system, classification, benefits, advantages and problems face the field of artificial neural networks will be reviewed in this section too. Section 2.4 will briefly summarize differences between expert systems and artificial neural networks. Finally, in section 2.5, we will describe the field of simulation. Furthermore, description, advantages and disadvantages of simulation will be discussed together with types of simulations and simulation environments.

2.1 Artificial Intelligence

2.1.1 Description of the field:

In general, artificial intelligence is a branch of science that enables computers to solve problems, learn from experience, recognize patterns in large amounts of complex data and make complex decisions based on human knowledge and reasoning skills. Additionally, artificial intelligence is constructing programs that can learn from their environment and respond to previously un-encountered situations in appropriate ways. Artificial intelligence searches the type of problems that cannot be solved with traditional algorithmic techniques. These are often problems in which quality is more important than the quantitative aspects. Therefore, artificial intelligence is concerned with qualitative rather than quantitative problem solving, with reasoning rather than calculation, with organizing large and varied amounts of knowledge rather than implementing a single well-defined algorithm.

Artificial intelligence is often divided into two major classes: strong artificial intelligence and weak artificial intelligence. In general, strong artificial intelligence argues that it is possible that one day a computer will be invented which can be called a mind in the fullest sense of the word. In other words, it can think, reason, imagine, etc., and do all the things that we currently associate with the human brain. Weak artificial intelligence, on the other hand, argues that machines can act as if they are intelligent and computers can only appear to think and are not actually conscious in the same way as human brains are. Strong artificial intelligence deals with the creation of some form of computer-based artificial intelligence that can truly reason and solve problems; a strong form of artificial intelligence is said to be sentient or self-aware. Moreover, strong artificial intelligence states that a computer with the right program would be mental. In contrast, weak artificial intelligence deals with the creation of some form of computer-based artificial intelligence that cannot truly reason and solve problems; such a machine would, in some ways, act as if it is intelligent, but it would not possess true intelligence or sentience. Furthermore, weak artificial intelligence just aims to solve problems not necessarily to be mental or model human behaviour.

Strong artificial intelligence* is trying to construct algorithms to find solutions to complex problems in a more human-like method and redefines intelligence to include more than just the ability to solve complex tasks or simply convince observers that such a quality exists within a system. Strong artificial intelligence rests upon the principle that complex machine systems such as neural networks are capable of establishing connections between different sets of data which were not previously programmed into the system. Therefore, from the strong artificial intelligence' point of view, systems that begin and continue to learn, creating and building a knowledge base have the ability to exhibit intelligent behaviour.

On the other hand, weak artificial intelligence is trying to construct programs that able to solve the problem regardless of the way it is achieved and whether or not the outcome is done in a human manner. Weak artificial intelligence is the science of incorporating "intelligent" aspects into non-intelligent systems to make them function at a higher, more efficient level. At this point, Intelligence is in quotes because the computer or program is not intelligent, it merely appears that way because of the sophistication of modern program design. For example a program may guess what the user is attempting to do or type because the previous attempts have been stored in memory.

While weak artificial intelligence provides us with cool little toys and makes our lives a little bit easier, it is not nearly as interesting as strong artificial intelligence. Strong artificial intelligence is the theory that it is possible to create a machine that can function at or at a higher level than humans in many-to-every aspect of life.

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* For further details about strong and weak artificial intelligence see: (Rich & Knight, 1991; Russell & Norvig, 1995).

2.1.2 Definitions of artificial intelligence:

Russell and Norving (1995, p.5) introduced definitions of artificial intelligence according to eight recent textbooks as shown in "table 2.1".

Systems that think like humans	**Systems that think rationally**
"The exciting new effort to make computers think… *machines with minds*, in the full and literal sense" (Haugeland, 1985). "[The automation of] activities that we associate with human thinking, activities such as decision making, problem solving, learning…etc."(Bellman, 1978).	"The study of mental faculties through the views of computational models" (Charniak and McDermott, 1985). "The study of computations that make it possible to perceive reason and act" (Winston, 1992).
Systems that act like humans	**Systems that act rationally**
"The art of creating machines that perform functions that require intelligence when performed by people" (Kurzweil, 1990). "The study of how to make computers do things at which, at the moment, people are better" (Rick and Knight, 1991).	"A field of study that seeks to explain and emulate intelligent behaviour in terms of computational processes" (Schalkoff, 1990). "The branch of computer science that is concerned with the automation of intelligent behaviour" (Luger and Stubblefield, 1993).

Table 2.1: Definitions of artificial intelligence.

Source: (Russell & Norving, 1995, p. 5).

Russel and Norvig (ibid, pp.5-8) classified different definitions for artificial intelligence by distinguishing the behaviour of the system (acting vs. thinking) and the way it behaves (human vs. rational). This distinction leads to four different approaches to artificial intelligence:

- **Acting humanly: The "Turing-test" approach**

This category is basically the area where the "Turing-test" can be applied to test the human characteristics of a program. This test consists of four main aspects:

- **Natural Language Processing** to enable it to communicate successfully in English (or some other human language);
- **Knowledge Representation** to store information provided before or during the interrogation;
- **Automated Reasoning** to use the stored information to answer questions and to draw new conclusions;
- **Machine Learning** to adapt to new circumstances and to detect and extrapolate patterns.

One should note that this test does not test the physical abilities. This is done by the total "Turing-test" which only works in connection with computer vision and robotics.

- **Thinking humanly: The cognitive modelling approach**

This category can also be covered by the field of cognitive science, which brings together computer models from AI and experimental techniques from psychology. Here, the goal is to imitate human thinking as closely as possible. It is not only the solution of a problem which is interesting, but how the program achieves this solution.

- **Thinking rationally: The laws of thought approach**

This field of AI is based on the Greek philosopher "*Aristotle*" who was one of the first to codify "right thinking". His famous syllogisms - for example, "*Socrates* is a man; all men are mortal; therefore Socrates is mortal."- (that had led later to the field of logic). There are two main obstacles pointed out here:

— Firstly, it is not easy to handle uncertain things (which obviously do exist in our world).

— Secondly, there is a big difference between being able to solve a problem in principle and doing so in practice.

- **Acting rationally: The rational agent approach**

Acting rationally means acting so as to achieve one's goals, given one's beliefs. According to "Russel" and "Norvig", the last category leads therefore towards a rational agent approach. In general, an agent is something that perceives and acts. Correct inference from the last category is only a part of a rational agent, because one way to act rationally is to reason logically to the conclusion that a given action will achieve one's goals, and then to act on that conclusion.

On the other hand, correct inference is not all of rationality; because there are often situations where there is no provably correct thing to do, yet something must still be done. There are also ways of acting rationally that cannot be reasonably said to involve inference. For example, pulling one's hand off of a hot stove is a reflex action that is more successful than a slower action taken after careful deliberation.

2.1.3 Goals of artificial intelligence:

Computers with some intelligence can be very useful for a number of purposes. For instance, they can help humans to reach decisions (task support) and they can perform tasks for a user without direct supervision. The goal of artificial intelligence is the design of systems that behave intelligently (Pollack, 1992). Moreover, the development of autonomous intelligent systems has been a primary goal of artificial intelligence (Wallace & Laird, 1999, p.117). Furthermore, artificial intelligence started as a field whose goal was to replicate human-level intelligence in a machine (Brooks, 1997, p. 395).

Therefore, the goal of artificial intelligence is often stated in terms of understanding intelligent behaviour in order to build adaptive intelligent systems* or autonomous agencies, which have their internal goal-structure and external behaviour that generally serves to achieve a goal and to operate independently

* For further details about artificial intelligence and cognitive architectures see: (Doyle & Dean, 1996; Chandrasekaran & Josephson, 1994; Gellatly, 1986).

from designers. And their performances on these tasks should be considered in somewhat intelligent by giving the principles that make intelligence possible. Concisely, one can say that the goal of artificial intelligence is designing computer systems that can perceive; learn; solve problems; make plans and can effectively imitate high-order human behaviour.

2.1.4 Applications of artificial intelligence:

There are many interesting applications in artificial intelligence, including: games, mathematics, intelligent agents, language translation, robotic surgery**,** scheduling systems, travel planning systems, package design, financial management systems, decision trees, routing diagrams, drive cars, recognize handwriting and spoken speech, and control factories. Briefly, some applications that are described by Watson and Blackstone (1989, p.449) as follow:

- **Robotics:**

Robotics involves the creation of machines that can move and relate to objects as humans can. The most frequent uses of robots include picking up items and placing them elsewhere, loading machines with items, performing repeated tasks such as welding, painting and assembling parts into a whole.

- **Vision systems:**

Vision systems provide machines with the ability to perceive using a camera connected to a computer. The image recorded by the camera is divided into many squares; each square is assigned a number depending on the intensity of its light reflection. These patterns are then compared against electronic templates of objects to determine the identity of the object. Some useful programs can work solely in two dimensions, but full computer vision requires partial three-dimensional information that is not just a set of two-dimensional views. In particular, computer vision is trying to build a system that can see as well as a human.

- **Natural language processing:**

Natural language processing focuses on machines understanding and responding to human commands. This important and heavily investigated artificial intelligence area has seen only limited results because human speech is highly context-dependent and ambiguous. Moreover, the field of natural language understanding tries to interpret human language to something a computer can understand and manipulate. The applications of this field are useful not only for testing theory on how human languages work but also to fit computers with more natural means of communication with humans.

- **Chess programs:**

For many years now, computer experts have been writing chess-playing programs with the aim of producing something which no human could beat. Chess is a challenge for programmers because its basic rules are so simple and well-defined and yet there is almost no limit to the refinement of chess skill (Sloboda, 1986, p. 206). Additionally, because chess program cannot compute all possible combinations, it is usually sufficient to combine three essential operations:

a. Generate static lists of legal moves.

b. Assess the value of a particular series of moves by means of evaluation functions that is assign numeric values to each given board position (there are four basic chess values that a computer must consider before deciding on a move: material, position, king safety and tempo).

c. Choose the move that yields the highest value.

2.1.5 Basic concepts of artificial intelligence:

In this section, the basic concepts of artificial intelligence that will be frequently used in the following chapters will be discussed.

- **Schemata:**

This concept goes back at least to 'Kant' as a description of mental concepts and mental categories (Smolensky, 1989, p.248). Schemata appear in many AI systems in the forms of frames, scripts, or similar structures; they are prepackaged bundles of information that support inference in stereotyped situations (ibid, p.248). Thus, a schema is a configuration of knowledge about objects and events, including general information (Haberlandt, 1994, p. 147).

- **Characteristics of schemata:**

The schema expresses typical information, not the unique features of a specific office, as an example. A schema usually includes sub-schemas; each of the objects in the office may be viewed as a schema. Schemas for physical objects like room, desk, and house are known as frames. Schemas for events are known as scripts.

Features of schemas:
Rumelhart and Ortony (through: Haberlandt, 1994, p. 147) list four basic features of schemas: • A schema has variables. • Schemas can include other schemas. • Schemas vary in their abstractness. • Schemas are flexible.

Table 2.2: Features of schemas.

- **Algorithms and heuristics:**

Anderson (1989, p.44) showed that the algorithms approach and the heuristics approach are broadly speaking sorts of strategy that may be employed in programming a computer to play games. Heuristic programming uses heuristics rules drawn from experience to solve problems. This is in contrast to algorithmic programming, which is based on mathematically provable procedures. Self-learning and getting better with experience characterize heuristic programming.

For some problems there is a known solution procedure which, if properly executed, guarantees a correct answer. Such procedures are known as algorithms. Most problems, however, cannot be cracked algorithmically, or if there is an algorithm it may be lengthy and difficult to operate. In such cases we usually grope our way towards a solution by calling upon various rules of thumb which go under the name of heuristics (Sloboda, 1986, p.177).

- **Description of algorithms:**

An algorithm is a procedure which guarantees a solution for members of some problem class. For instance, most of us learned algorithms for solving long multiplication when we were at school. If one follows all the steps in the right order and makes no calculation errors then one always ends up with the right answer (Sloboda, 1986, p. 206). Therefore, one can program the machine to try all the possible moves in a game one after another until it comes up with the optimum move in any particular situation (Anderson, 1989, p.44). However, many important computational problems can be solved algorithmically. But many others cannot, for theoretical or practical reasons (Haugeland, 1996, p.13). Generally, an algorithm is suitable for situations where the number of moves and variables to consider (and hence calculations to perform) is relatively small (Anderson, 1989, p.45).

Sloboda (1986, p. 206) discussed the relationship between algorithm and chess by discussing the following question: "Is there an algorithm for chess? well, in theory there is. It involves considering each alternative move, then each possible reply by your opponent, then each possible reply you could make, and so on, until you had explored the consequences of every possible move right through to the point where one or other player won. You would then choose the move associated with the largest number of winning outcomes.

Unfortunately, such an algorithm is unworkable. Someone has calculated that there are more possible chess games than there are atoms in the universe. Even if one only looked five moves ahead one would have to consider up to 50,000,000 different combinations of moves. It would probably take even the fastest existing computer with unlimited storage space, several million years to play a game of chess using such an algorithm."

- **Description of heuristics:**

George Polya (see: Luger & Stubblefield, 1989, p. 149) defines heuristic as: "the study of the methods and rules of discovery and invention". This meaning can be traced to the term's Greek root, the verb "eurisco", which means "I discover". When "*Archimedes*" emerged from his famous bath, he shouted "Eureka!"- meaning "I have found it!".

In order to reduce the search space in problems (such as chess), what one usually needs are heuristics. These are like rules of thumb which have a reasonable probability of producing acceptable results. It is pretty clear that human problem-solving normally proceeds with a large helping of heuristics, and such heuristics are the usual stock in trade of coaches (Sloboda, 1986, pp. 206-207). In the case of chess, sensible heuristics involve looking ahead a few moves in various directions and then evaluating factors like number and kind of pieces, mobility, control of the center, pawn coordination, and so on. These are not infallible measures of the strength of chess positions; but, in combination, they can be pretty good. This is how chess-playing computers work—and likewise many other machines that deal with problems for which there are no known algorithmic solutions (Haugeland,1996,p.14).

Luger and Stubblefield (1989, pp. 149-150) showed that Al problem solvers employ heuristics in two basic situations:

1- A problem may not have an exact solution because of inherent ambiguities in the problem statement or available data. Medical diagnosis is an example of this. A given set of symptoms may have several possible causes; doctors use heuristics to choose the most likely diagnosis and formulate a plan of treatment.

2- A problem may have an exact solution, but the computational cost of finding it may be prohibitive.

- **Characteristics of heuristics:**

1- Many human problems are too ill-defined for algorithms to apply. Often we are unaware of all the possibilities available to us and so cannot evaluate all the alternative courses of action. Even when we can do this, it may take far long or take up too many mental resources. Heuristics offer the prospect of rapid response to a situation. In the real world one rarely has unlimited time to decide (Sloboda, 1986, p. 207).

2- The practical reason for using heuristics is that, in many games, the number of possible moves is too great to allow the machine to use an algorithm, even if the algorithm is known. Therefore, heuristic search limited the search to a small subset of a very large universe of possibilities on the basis of external information (Widman & Loparo, 1989, p.7).

3- Heuristics are guides to action that have been acquired through experience. Their advantages include simplicity and familiarity, and their weakness is that we can never know in advance whether they will lead us in the right direction (Sloboda, 1986, p.177).

- **Production rules:**

Formally, a production rule consists of an "IF" clause and a "THEN" clause. The "IF" clause includes a set of conditions that must be met in order to execute the actions specified in the "THEN" clause (Haberlandt, 1994, p.156). Production rules have the general form (If x is true, then y is true; or If x is true; then produce y.). And because a skill has many components, many rules are needed to describe it adequately (ibid, p.156). The principal mechanism for problem solving in artificial intelligence is the production system, which consists of three modular elements: a global data base, a set of production rules, and a set of control structures (Wagman, 1993, pp. 15-16).

Summary:

In the previous part, the basic fundamentals and aspects of artificial intelligence were briefly discussed. In the next two parts, additional discussion about the two basic approaches of artificial intelligence, expert system and artificial neural networks, will be concisely demonstrated.

2.2 Expert Systems

2.2.1 Description and definitions:

Expert systems are knowledge-based information systems that use a knowledge base about a specific complex application area to act as an expert consultant to end users. In addition, a clear definition of an expert system determined by 'Feigenbaum' (through: Wagman, 1993, p.126) was:

"An intelligent computer program that uses knowledge and inference procedures to solve problems that are difficult enough to require significant human expertise for their solution".

Briefly, Watson and Blackstone (1989, p.465-74) indicated that expert systems are developed using the following steps:

1. Identify an appropriate problem.
2. Develop a prototype system.
3. Develop the complete system.
4. Evaluate the system.
5. Integrate the system.
6. Maintain the system.

Table 2.3: Steps towards developing an expert system.

In other words, expert systems, or knowledge-based systems, are programs that reproduce the behaviour of a human expert within a narrow domain of knowledge (Widman & Loparo, 1989, p.9).

2.2.2 Characteristics of expert systems:

Expert systems are rule-based logic programs that are designed to solve problems or make recommendations within a specific knowledge domain. Human experts determine which parts of the knowledge domain are pertinent for the system, and those are gathered into a knowledge base. An inference engine processes and combines facts related to a particular problem, case or question with the knowledge from the knowledge base in order to come up with an answer. This requires that the inference engine link pieces of relevant knowledge in order to build a chain of logic leading to a valid conclusion.

Typically, an expert system consists of two parts, an inference engine, and a knowledge base (Widman & Loparo, 1989, p.126). The inference engine is generic. Inference is performed through a logical chaining of "If-Then" rules that are acquired from an expert. The logic on which these systems are based is deterministic. It handles the user interface, external files, program access, and scheduling. The knowledge base contains the information that is specific to a particular problem. This knowledge base allows an expert to define the rules which govern a process.

The system can operate in one of two modes: A data-driven forward chaining mode, in which known data is input to determine if some conclusion may be reached; or, a goal-drive back-chaining mode, to determine if a given outcome has the necessary and sufficient supporting input data (ibid).

An expert system is faster and more consistent and can have the knowledge of several experts. Moreover, it operates under various conditions and disturbances, and incorporates human expertise and thinking into their decision-making process. Of course, it does not get tired or distracted by overwork or stress. An expert system can solve real-world problems using human knowledge and following human reasoning skills.

2.2.3 Advantages and benefits of expert systems:

Beginning in the 1980s, the use of expert systems has proliferated in the sciences, medicine, psychology, law, engineering, finance, architecture and other professions (Wagman, 1993, p.127).

Watson and Blackstone (1989, p.471) indicated that there are many potential benefits that can result from developing expert systems such as: **i)** Freeing personnel for other activities. **ii)** Saving money, time spent on the decision-making activity and providing decision-making skills that are in short supply. **iii)** Moving toward more nearly optimal decision making and increasing decision-making consistency. **iv)** Providing a model for training new personnel in decision making and providing a standard of performance for control purposes.

Table 2.4: Benefits of expert systems.

In the following, some advantages of expert system will be shown:

- The economic advantage is that expert systems are less expensive than human expertise; they are reliable and do not show the degradation in performance that accompanies human fatigue, overwork, and stress (Wagman, 1993, p.127).
- A model also can be used for training personnel in appropriate decision-making behaviour. For example, the model can be shown to a novice decision maker to illustrate the decision-making heuristics that have been employed in the past. In a training program the novice can be given structured decision cases, asked to make decision and presented with the decisions made by the model. The process can be repeated until the decisions made by the novice and the model converge (Watson & Blackstone, 1989, p.472).
- An expert system also can be used to monitor decisions made by humans. The decisions made by the model can be compared to the human's with exception reports being generated when deviations are noted. This procedure might be desirable with novice decision makers or when there are multiple decision makers acting according to prescribed guidelines (ibid, p.472).
- Expert systems had the potential to interpret statistics, in order to formulate rules. Moreover, expert systems can analyze survey results, and will do it accurately and can very quickly propose recommendations for the inclusion of survey topics.

2.2.4 Applications of expert systems:

Expert systems have been built to solve a range of problems in domains such as medicine, mathematics, engineering, chemistry, geology, computer science, business, law, defense, and education. These programs have addressed a wide range of problem types (Luger & Stubblefield, 1989, p. 293). Expert Systems use the specialist knowledge that people like doctors and lawyers have in order to assist other people by giving advice on those subjects. For example, Medical expert systems have a task that is to organize and present all the relevant records for a particular patient to the physician. Furthermore, Medical expert systems have been developed to analyze the disease symptoms, medical history, and laboratory test results of a patient, and then suggest a variety of possible diagnosis to the doctor. “Table 2.5” shows an example demonstrated by Waterman (through: Wagman, 1993, p.129) as an application of expert system in Medicine.

Name	**Medicine**
PUFF:	Diagnosis lung disease.
VM:	Monitors intensive-care patients.
ABEL:	Diagnosis acid-base/electrolytes.
AI/COAG:	Diagnosis blood disease.
Al/RHEUM:	Diagnosis rheumatoid disease.
CADUCEUS:	Diagnosis internal medicine disease.
ANNA:	Monitor digitalis therapy.
BLUE BOX:	Diagnosis/remedy depression.
MYCIN:	Diagnosis/remedy bacterial infections.
ONCOCIN:	Remedy/manage chemotherapy patients.
ATTENDING:	Instruct in anesthetic management.
GUIDON:	Instruct in bacterial infections.

Table 2.5: Expert systems in medicine.

Source: (Wagman, 1993, p.129).

In addition, the following list (Widman & Loparo, 1989, p.9; Luger & Stubblefield, 1989, p. 293) includes the types of problems to which expert systems have been applied:

- **Control:** Performing real-world interventions to achieve desired goals and governing the behaviour of a complex environment.
- **Design:** The making of specifications to create objects that satisfy particular requirements and/or to meet certain performance goals.

- **Instruction:** Teaching new concepts and information to non-experts. For example, detecting and correcting deficiencies in students' understanding of a subject domain.
- **Interpretation:** Analysis of data to determine their meaning and forming high-level conclusions or descriptions from collections of raw data.
- **Monitoring:** Comparing the observed behaviour of a system to its expected behaviour.
- **Planning:** Creation of programs of actions that can be carried out to achieve goals.
- **Prediction:** Projecting probable consequences of given situations. In other words, forecasting the course of the future from a model of the past and present.
- **Repair:** Prescription of real-world interventions to resolve problems.
- **Diagnosis:** Determining the cause of malfunctions in complex situations based on observable symptoms.

2.2.5 Deficiencies and limitations of expert systems:

Luger and Stubblefield (1989, p.17-18) demonstrated the following deficiencies of expert systems:

- Difficulty in capturing "deep" knowledge of the problem domain. MYCIN, for example, lacks any real knowledge of human physiology. It does not know what blood does or the function of the spinal cord. Folklore has it that once, when selecting a drug for treatment of meningitis, MYCIN asked if the patient was pregnant, even though it had been told that the patient was male.
- Lack of robustness and flexibility. If humans are presented with a problem instance that they cannot solve immediately, they can generally return to an examination of first principles and come up with some strategy for attacking the problem. Expert systems generally lack this ability.

- Inability to provide deep explanations. Because expert systems lack deep knowledge of their problem domains, their explanations are generally restricted to a description of the steps they took in finding a solution. They cannot tell "why" a certain approach was taken.

- Difficulties in verification. While the correctness of any large computer system is difficult to prove, expert systems are particularly difficult to verify. This is a serious problem, as expert systems technology is being applied to critical applications such as air traffic control, nuclear reactor operations, and weapons systems.

- Unlike a human being, however, current programs cannot learn from their own experience; their knowledge must be extracted from humans and encoded in a formal language (Luger & Stubblefield, 1989, p.291-292). In other words, an expert system has inability to learn from its errors (Widman & Loparo, 1989, p.13) and it must be taught new knowledge and modified as new expertise is needed.

2.3 Neural Networks

2.3.1 Introduction:

In the past few years the approach to cognitive science and artificial intelligence known as connectionist modeling has dramatically increased its influence (Smolensky, 1989, p.233). Connectionist systems are networks of lots of simple active units that have lots of connections among them, by which they can interact. There is no central processor or controller, and also no separate memory or storage mechanism. The only activity in the system is these little units changing state, in response to signals coming in along those connections, and then sending out signals of their own (Haugeland, 1996, p.21).

2.3.2 Connectionism framework:

The goal of connectionist research is to model both lower-level perceptual processes and such higher-level processes as object recognition, problem solving, planning, and language understanding (Smolensky, 1989, p.233). In addition, the basic strategy of the connectionist approach is to take as its fundamental processing unit something close to an abstract neuron (Rumelhart, 1989, p.207). Rumelhart (ibid, p.209) demonstrated seven major components of any connectionist system:

- A set of processing units;
- A state of activation defined over the processing units;
- An output function for each unit that maps its state of activation into an output;
- A pattern of connectivity among units;
- An activation rule for combining the inputs impinging on a unit with its current state to produce a new level of activation for the unit;
- A learning rule whereby patterns of connectivity are modified by experience; and
- An environment within which the system must operate.

2.3.3 Fundamentals of neural networks:

Neural networks try to simulate a part of a natural brain with neurons, synapses and dendrites. It consists of several layers of so called units, where one layer is the input layer and one is the output layer (Russell & Norving, 1995). The layers in the middle are called hidden layers as shown in "figure 2.3". From every layer to the next, every unit (i.e., neuron) is connected by a weighted joint to every unit in the above layer. Every unit sums up the incoming signals and produces and output signal (continuous or discrete) dependent on the activation function which is assigned to the units. This activation function is usually chosen among the step, sign or sigmoid function. Learning in neural networks is the process of updating the weights between the units (see figures 2.1 and 2.2).

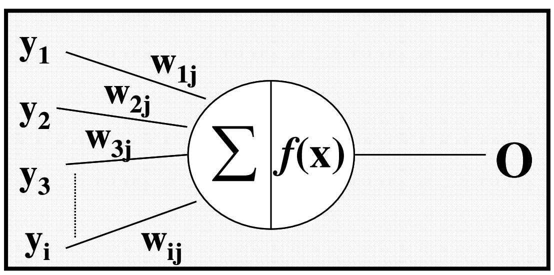

Figure 2.1: An example of a neuron model.

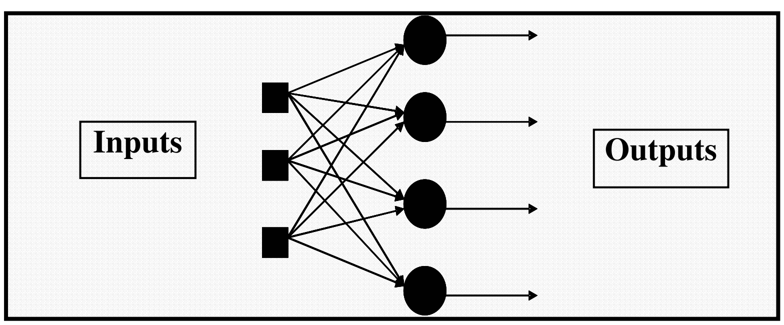

Figure 2.2: An example of a single-layer network.

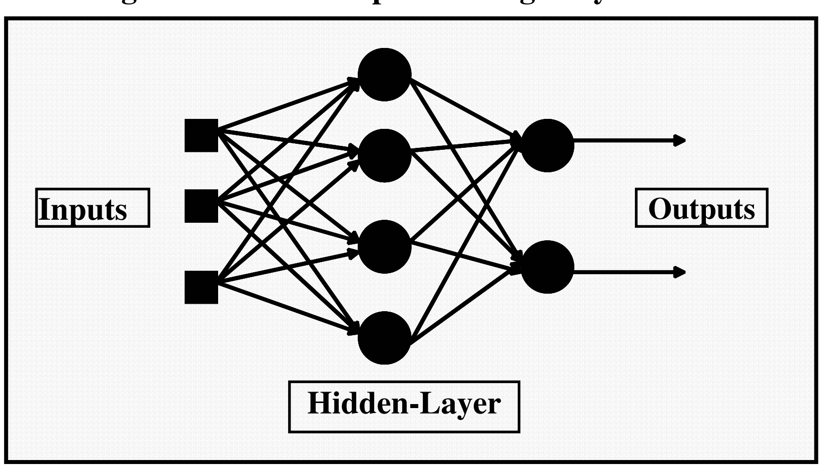

Figure 2.3: An example of a hidden-layer network.

Neural networks can be trained to give the correct response for each input by applying training examples. Difficulties with neural networks arise when deciding about the structure of the neural networks, the number of input and output units and the number and size of the hidden layers (Niederberger & Gross, 2002, pp. 13-14).

The neural network learns by modifying its sets of weights and/or threshold characteristics in response to the correctness of its classification. Correct classifications reinforce (increase) the weights that led most strongly to the final result. Incorrect classifications do the opposite. There are many types of weight adjustment algorithms, or "learning rules" (Widman & Loparo, 1989, p.14).

2.3.4 Characteristics of connectionist system:

- **The set of processing units:**

Any connectionist system begins with a set of processing units. Specifying the set of processing units and what they represent is typically the first stage of specifying a connectionist model. In some systems these units may represent particular conceptual objects such as features, letters, words, or concepts; in others they are simply abstract elements over which meaningful patterns can be defined. A unit's job is simply to receive input from its neighbors and, as a function of the inputs it receives, to compute an output value, which it sends to its neighbors. The system is inherently parallel in that many units can carry out their computations at the same time. Within any system we are modeling, it is useful to characterize three types of units: input, output, and hidden units. Input units receive inputs from sources external to the system under study. These inputs may be either sensory inputs or inputs from other parts of the processing system in which the model is embedded. The output units send signals out of the system. They may either directly affect motoric systems or simply influence other systems external to the ones we are modeling. The hidden units are those whose only inputs and outputs are within the system we are modeling.

- **The state of activation:**

In addition to the set of units we need a representation of the state of the system at time (t). This is primarily specified by a vector a (t), representing the pattern of activation over the set of processing units. Each element of the vector stands for the activation of one of the units. It is the pattern of activation over the whole set of units that captures what the system is representing at any time. It is useful to see processing in the system as the evolution, through time, of a pattern of activity over the set of units.

Different models make different assumptions about the activation values a unit is allowed to take on (Rumelhart, 1989). Activation values may be continuous or discrete. If they are continuous, they may be unbounded or bounded. If they are discrete, they may take binary values or any of a small set of values. Thus in some models units are continuous and may take on any real number as an activation value. In other cases they may take on any real value between some minimum and maximum such as, for example; the interval (0, 1). When activation values are restricted to discrete values, they most often are binary—such as the values (0) and (1), where (1) is usually taken to mean that the unit is active and (0) is taken to mean that it is inactive.

- **The output function:**

Units interact by transmitting signals to their neighbors. The strengths of signals, and therefore the degree of which they affect their neighbors, are determined by their level of activation (Rumelhart, 1989, pp.210-212). Connectionist systems are large networks of extremely simple computational units, massively interconnected and running in parallel (Smolensky, 1989, p.233). Each unit or processor has a numerical activation value which it communicates to other processors along connections of varying strength; the activation value of each processor constantly changes in response to the activity of the processors to which it is connected. The values of some of the units form the input to the system, and the values of other units form the output; the connections between the units determine how input is transformed to output (ibid, p.233). Briefly, in connectionist systems, knowledge is encoded not in symbolic structures but rather in the pattern of numerical strengths of the connections between units.

2.3.5 Training stages of a neural network:

The process of training a neural network involves the following stages:

1. The untrained network is presented with carefully selected patterns of typical input data.
2. The network maps the data into an initial pattern of output data.
3. The network adjusts the weights of its connections using a variety of functions and according to how much the resulting output patterns differ from what they are expected to be. A training file is developed, consisting of data for each input node and the desired response for each of the network's output nodes. The adjustment of the weights is a matter of trial-and-error, does not follow rigidly programmed instructions and involves no software programming.
4. Step (3) is repeated for many typical input patterns, so that the actual output of the network converges with the desired (by the trainer) output. When the gap between actual output and desired output falls below a pre-established (by the trainer) threshold of accuracy, the training process is complete. As a result, the network operates satisfactorily and is ready to be used as a predictive or diagnostic tool. As well, it is ready to process new selections of the kind of input patterns for which it has bee trained (Floridi, 1999).

2.3.6 Classification of artificial neural networks:

There are two major learning methods for neural networks: supervised and unsupervised. The supervised learning approach is most commonly used and it requires historical data with examples of both inputs and outputs to train the model. It is used to build prediction, classification and time series models. It is called supervised learning because during training, the network can compare the predicted results to the actual results and adjust the model accordingly. Unsupervised learning does not have known answers to train the model but instead creates its own interpretation and validation of the data. Unsupervised learning is often used for grouping data.

Depending on their methods of data processing and training, artificial neural networks can be classified as:

- **Feed-forward:** When they have no feedback and simply associate inputs with outputs. These types of artificial neural networks are normally used for simple pattern recognition.
- **Recurrent:** When they implement feedback relations needed in order to create a dynamic system that will produce the appropriate pattern.
- These types of neural networks are normally used for pattern reconstruction:
- **Supervised:** When they require a human trainer to adjust the artificial neural networks to the desired output. The most widely used supervised artificial neural networks are known as Back Propagation artificial neural networks. They are multi-layered, feed-forward networks that are trained using an error criterion. The network's output is compared with the desired output to produce an error measure; then an algorithm propagates the error from the output to the input in order to adjust the weights increasingly well so as to reduce the error. The network is trained by repeating this process many times. Once the error parameter has decreased below a specified optimal threshold, the network is said to have converged and its training is complete. Back Propagation artificial neural networks are used for classification and prediction tasks.
- **Self-organizing:** When they can learn to identify structures in the data by adapting automatically in response to particular types of inputs, according to pre-established requirements (Floridi, 1999).

Rumelhart (1989, p.213) explained that changing the processing or knowledge structure in a connectionist system involves modifying the patterns of interconnectivity. In principle this can involve three kinds of modification:

(1) Development of new connections.

(2) Loss of existing connections.

(3) Modification of the strengths of connections that already exist.

2.3.7 Benefits of neural networks:

Neural networks show both promise and a number of yet unresolved difficulties. In addition to the fact that connectionist systems are capable of exploiting parallelism in computation and mimicking brain-style computation, such systems are important because they provide good solutions to a number of very difficult computational problems that seem to arise often in models of cognition. In particular they typically are good at solving constraint-satisfaction problems; are efficient mechanisms for best-match search, pattern recognition, and content-addressable memory; automatically implement similarity-based generalization; offer simple, general mechanisms for adaptive learning; and exhibit graceful degradation with damage or information over load (Rumelhart, 1989, pp.215-216).

Moreover, Luger and Stubblefield (1989, p. 584-585) demonstrated the following benefits of neural networks:

- They handle noise well. Once trained, neural nets show an ability to recognize patterns even though part of the input data is missing or obscured.
- They provide a tool for modeling and exploring brain function, much as production systems have helped cognitive scientists study higher-level cognitive processes.
- By patterning themselves after the architecture of the brain, they provide a plausible model of intelligent mechanism.
- They are robust. Because the information is distributed, neural nets can survive the failure of some nodes.
- They are a promising model of associative memory.

- They are able to learn new concepts.
- In addition, they have had success in areas like vision that have frustrated more traditional approaches.

Briefly, from the previous discussion, one can summarize the characteristics of artificial neural networks as follow:

1- Parallelism. 2- Capacity for adaptation. 3- Distributed memory.
4- Ability to learn. 5- Capacity for generalization.

2.3.8 Advantages of neural networks:

Neural network technology has proven to be very effective in pattern recognition tasks such as handwriting recognition and modeling of seemingly serial human behaviour such as touch typing and verb conjugation and may provide an important new tool for tasks that require learning by the program (Widman & Loparo, 1989, p.14).

Neural networks can provide a lower-level model of intelligent mechanism, and they have already made progress toward modeling perception and associative memory (Luger & Stubblefield, 1989, p. 586).

In addition, artificial neural networks are useful for problems such as physical processes that do not have algorithmic interpretations or algorithmic interpretations are too complex and difficult to be found. They are used in specific paradigms: recognition of speakers in communications; texture analysis; three-dimensional object recognition; handwritten word recognition; and facial recognition. Moreover, artificial neural networks create their own relationship among information and can work with large numbers of variables or parameters.

Real world applications of artificial neural networks technology include voice and visual recognition, chemical structures, biomedical instrumentation, medical diagnosis, credit rating, forecasting of future sales, investment analysis (where predictions can be attempted on the basis of patterns provided by past data), market performance, economic indicators, writing recognition (especially signature verification, when new signatures need to be compared with those stored), automatic control and monitoring. Best-Match Search is considered one of the most advantages of artificial neural networks. The following is concisely conclusion of this feature.

Best-Match Search:

Best-Match Search, using neural networks, can be used to find stored data that match some target or probe. Rumelhart (1989, p.222) explained the process as the following:

- When a previously stored (that is, familiar) pattern enters the memory system, it is amplified, and the system responds with a stronger version of the input pattern. This is a kind of recognition response.
- When an unfamiliar pattern enters the memory system, it is dampened, and the activity of the memory system is shut down. This is a kind of unfamiliarity response.
- When part of a familiar pattern is presented, the system responds by “filling in” the missing parts. This is a kind of recall paradigm in which the part constitutes the retrieval cue, and the filling in is a kind of memory-reconstruction process. This is a content-addressable memory system.
- When a pattern similar to a stored pattern is presented, the sys tem responds by distorting the input pattern toward the stored pattern. This is a kind of assimilation response in which similar inputs are assimilated to similar stored events.
- Finally, if a number of similar patterns have been stored, the system will respond strongly to the central tendency of the stored patterns, even though the central tendency itself was never stored. Thus this sort of memory system automatically responds to prototypes even when no prototype has been seen.

Rumelhart (ibid) believed that these properties correspond very closely to the characteristics of human memory and are exactly the kind of properties we want in any theory of memory.

2.3.9 Problems challenge the field of artificial neural networks:

Because of the previous advantages, research in neural networks is growing rapidly and promises to contribute valuable insights to artificial intelligence as a whole. However, Luger and Stubblefield (1989, p. 585) indicated that a number of problems must be addressed if this work is to continue to grow:

- Neural nets are not brains, in spite of their surface similarity to human neural systems. Brains have a different, more complex structure; they are highly modular, and there is growing evidence that they not only learn by adjusting weights on connections but also are able to grow new connections.
- Neural nets can not now model higher-level cognitive mechanisms, like attention, symbols, reference. Whether or not humans prove to be physical symbol systems, they are very good at producing and manipulating symbols; how can this be done in a simulated network? Also, it is not clear how networks can represent mechanisms like focus of attention.
- Neural nets may be at the wrong level of abstraction; they may be too weak to describe higher-level processes.
- Higher-level organization and abstractive principles do not disappear. Humans reason from class taxonomies and rules of performance. The brain itself is a highly structured and organized system. It is unlikely that any progress in intelligence will come without an understanding of the principles of this organization.
- Some human intellectual activity may not be parallel. Much higher-level reasoning and problem-solving behaviour seems to be quite serial in nature. In these cases, a production system approach may be much more fruitful.
- Brains are very large, having trillions of neurons. Although we can certainly achieve useful behaviour from smaller systems, the complexity of more highly intelligent programs may require more neurons than we could efficiently implement on a computer. Higher-level symbolic descriptions may ultimately prove more efficient to design and implement.

- Although neural architectures obviously underlie human intelligence, they may not be the best abstraction for implementing it on a machine.

Moreover, two major limitations of the neural network approach are that the network can not be “told” facts, as can conventional expert systems, and that “knowledge” in the network is not easily available to the user. Unlike a symbolic Al system, the neural network elements can not “explain” their numeric weighting factors. This latter limitation can be partially overcome by examining the weights of a mature network to characterize the strengths of the relationships between inputs and outputs (Widman & Loparo, 1989, p.14).

2.4 Differences between expert systems and artificial neural networks

2.4.1 Structure:

A neural net is a set of nodes and connections that store experimental knowledge obtained by training on task examples. An expert system is a set of deductive rule-bases, which follows sets of instructions and hence require programs in order to perform its computations. Furthermore, since expert systems have explicit rules, it is easy to understand how their decisions are made. By contrast, a faulty neurocomputing system might need nothing more than additional nodes, connections, or training-set examples, requiring no particular insight to add to the system.

2.4.2 Data distribution:

Unlike expert system, which requires a programmer to assume frequently a certain form to the data and test its validity until the correct form is found; neural networks do not require assumptions about the form or distribution of the data to analyze it. Moreover, neural networks are more tolerant of imperfect data, such as the presence of missing values or other data quality problems. Furthermore, neural networks perform better than traditional statistical methods when the form of the data is unknown or non-linear, or when the problems are complex with highly interrelated relationships.

2.4.3 Adaptability:

Neural networks are flexible tools in a dynamic environment, and have the capacity to learn rapidly and change quickly. As circumstances, data values and outcomes change, the model quickly learns and adapts to constantly changing information by modifying connection weights. On the other hand, rule based systems are limited to the specific situation for which they were designed, and the learning process seems difficult to simulate. To facilitate, when conditions change, they are no longer valid.

2.4.4 Processing:

Expert systems process problem rule at a one time, sequential, using “If-Then” rules. In contrast, neural networks is called parallel processing.

2.5 Simulation

2.5.1 Description:

Simulation has become ever more prominent as a method for studying complex systems in which uncertainty is present. In other words, computer simulation is the problem-solving process of predicting the future state of a real system by studying an idealized computer model of the real system (Widman & Loparo, 1989, p.15). In this manner, the purpose of simulation experiments is to understand the behaviour of the system or evaluate strategies for the operation of the system. Additionally, simulation is an interdisciplinary subject, using ideas and techniques from statistics, probability, and computer science. Simulation is one of the most frequently used management science techniques, and every indication shows that its popularity is growing (Watson & Blackstone, 1989, p.15). Furthermore, simulation experiments are usually performed to obtain predictive information that would be costly or impracticable to obtain with real devices (Widman & Loparo, 1989, p.15). Moreover, simulation is used when there are only poor mathematical modeling alternatives (Watson & Blackstone, 1989, p.15).

Simulation gives an overview of the real system using statistics, estimating probabilities of events (e.g. risks), and testing a model. Simulations are usually referred to as either discrete event or continuous, based on the manner in which the state variables change. Discrete event refers to the fact that state variables change instantaneously at distinct points in time. In a continuous simulation, variables change continuously, usually through a function in which time is a variable. In practice, most simulations use both discrete and continuous state variables, but one of these is predominant and drives the classification of the entire simulation.

Simulation allows us to ask many “what if” questions about changes in our systems without actually changing the systems themselves. Thus, it is useful to understand the current system and explain why it is behaving as it is, and to explore changes to try to improve it. Finally, simulation models contain equations that express relationships between variables of interest (Watson & Blackstone, 1989, p.22).

2.5.2 Advantages and disadvantages of simulation:

Watson and Blackstone (1989, p.16) demonstrated the following advantages of simulation:

1- It is possible to experiment on a system without exposing the organization to real-world dangers. For this reason, simulation has been referred to as “the manager’s laboratory”.

2- By investigating possible changes in a real-world system through a simulation model, we can often learn how to improve the behaviour of a system without actually trying out both good and bad proposals on the system.

3- It is easier to control experimental conditions in a simulation model than in a real-world system.

4- In a simulation model it is possible to compress long periods of time into seconds of computer time. As an example, consider a new product proposal. A simulation model can describe quickly the product’s movement through the introduction, growth, maturity, and decline stages of the product life cycle.

Moreover, compared to experimenting with the actual system, simulation is often the only possibility, because it is much more flexibility to try things out before building the actual system. It has flexibility to control different variables, and it is helpful to understand the actual system, and it allows the analysis of a system’s capabilities, capacities, and behaviours without requiring the construction of or experimentation with the real system. In addition, simulation makes it possible to study more complicated models, which do not have an analytical solution (or solution is difficult), and it does not have to make as many simplifying assumptions (For further details see: Law & kelton, 1982, p.8). However, despite the advantages of simulation presented above, simulation has also disadvantages. For example: It can take long time to simulate a problem and systems with many particles and long time scales are problematical.

2.5.3 Building a computer simulation:

Within the overall task of simulation, there are essential processes for building a computer simulation*. In this section, these processes will be described as discussed by Law and Kelton (1982):

Define problem space.

The first step in developing a simulation is to explicitly define the problem that must be addressed by the model. The objectives and requirements of the project must be stated along with the required accuracy of the results. Boundaries must be defined between the problem of interest and the surrounding environment. Interfaces must be defined for crossing these boundaries to achieve interoperability with external systems. A model can not be built based on vague definitions of hoped for results.

Define conceptual model.

Once the problem has been defined, one or more appropriate conceptual models can be defined. These include the algorithms to be used to describe the system, input required, and outputs generated. Assumptions made about the system are documented in this phase, along with the potential effects of these assumptions on the results or accuracy of the simulation. Limitations based on the model, data, and assumptions, are clearly defined so that appropriate uses of the simulation can be determined.

The conceptual model includes a description of the amount of time, number of personnel, and equipment assets that will be required to produce and operate the model. All potential models are compared and trade-offs made until a single solution is defined that meets the objectives and requirements of the problem and for which algorithms can be constructed and input data acquired.

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* For further details about building computer simulation see (Banks, 1997; Banks, 1999; Banks, 2001).

Collect input data.

Once the solution space has been determined, the data required to operate and define the model must be collected. This includes information that will serve as input parameters, aid in the development of algorithms, and be used to evaluate the performance of the simulation runs. This data includes known behaviours of working systems and information on the statistical distributions of the random variates to be used. Collecting accurate input data is one of the most difficult phases in the simulation process, and the most prone to error and misapplication.

Construct software model.

The simulation model is constructed based on the solution defined and data collected. Mathematical and logical descriptions of the real system are encoded in a form that can be executed by a computer. The creation of a computer simulation, as with any other software product, should be governed by the principles of software engineering.

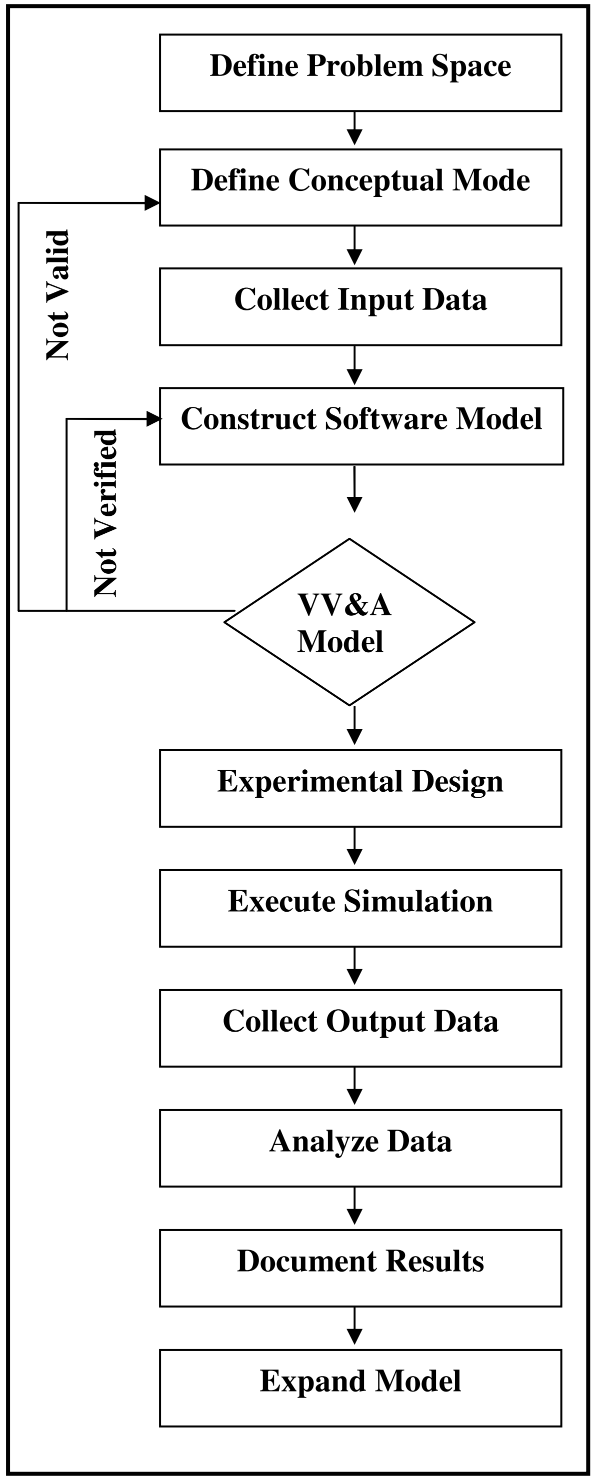

Figure 2.4:
Simulation development process.

Verification, validation and accreditation of the model.

Verification, validation, and accreditation (VV&A), is an essential phase in ensuring that the model algorithms, input data, and design assumptions are correct and solve the problem identified at the beginning of the process. Since a simulation model and its data are the encoding of concepts that are difficult to completely define, it is easy to create a model that is either inaccurate or which solves a problem other than the one specified. The VV&A process is designed to identify these problems before the model is put into operation. Validation is the process of determining that the conceptual model reflects the aspects of the problem space that need to be addressed and does so such that the requirements of the study can be met. Validation is also used to determine whether the operations of the final software model are consistent with the real world, usually through experimentation and comparison with a know data set. Verification is the process of determining that the software model accurately reflects the conceptual model. Accreditation is the official acceptance of the software model for a specified purpose. A software model accredited for one purpose may not be acceptable for another, though it is no less valid based on its original design.

Design experiments.

This phase identifies the most productive and accurate methods for running the simulation to generate the desired answers. Statistical techniques can be used to design experiments that yield the most accurate and uncompromised data with the fewest number of simulation runs. When simulation runs are expensive and difficult to schedule, experimental design can ensure answers at the lowest cost and on the shortest schedules.

Execute simulation.

This is the actual execution of the designed, constructed, and validated model according to the experimental design. The simulation runs generate the output data required to answer the problem initially proposed. In the case of Monte

Carlo models, many hundreds or thousands of replications may be required to arrive at statistically reliable results.

Collect output data.

Concurrent with the execution of the model, output data is collected, organized, and stored. This is sometimes viewed as an integral part of the model, but should be distinctly separated since it is possible to change the data collected without changing the model algorithms or design.

Analyze data.

Data collected during the execution of a simulation can be voluminous and distributed through time. Detailed analyses must be performed to extract long-term trends and to quantify answers to the driving questions that motivated the construction of the simulation. Analysis may produce information in tabular, graphic, map, animation, and textual summary forms. Modern user interfaces have greatly enhanced this phase by displaying data in forms that can be easily understood by diverse audiences.

Document results.

The results of the simulation study or training session must be documented and disseminated to interested parties. These parties identify the degree to which the simulation has answered specific questions and areas for future improvements.

Expand model.

Simulation models are expensive and difficult to build. As a result, once a model is built, it will be modified for use on many related projects. New requirements will be levied, new users will adopt it, and the entire development process will be conducted many times over.

2.5.4 Types of simulations:

There are two major types of simulation: continuous and discrete. Continuous simulation predicts the behaviour of systems described by differential equations, such as thermal, mechanical, analog electrical and fluid devices.

Moreover, it concerns the modeling over time of a system by a representation in which the state variables change continuously with respect to time. Discrete-event simulation concerns the modeling of a system as it evolves over time by a representation in which the state variables change only at a countable number of points in time (law & Kelton, 1982, p.4).

Discrete simulation predicts the behaviour of event-driven systems, such as manufacturing plants, message traffic on networks, and purposeful movements of people such as in bank queues. Discrete simulation also is used to simulate intelligent agents such as opposing military command centers, competing commercial organizations, and espionage—counterespionage net works (Widman & Loparo, 1989, p.16).

2.5.5 Simulation environments:

An important issue when constructing an agent is the environment in which the agent will act (Niederberger & Gross, 2002, p.32). In this section, we will briefly review several different kinds of environment that are discussed by Niederberger and Gross (ibid), and Russell and Norving (1995, p.46):

1. **Fully observable vs. partially observable:**

An environment is fully observable if the agent's sensors give it access to the complete state of the environment at any point in time. If all aspects that are relevant to the choice of action are able to be detected then the environment is effectively fully observable. Noisy and inaccurate sensors can result in partially observable environments. A fully observable environment is convenient because the agent need not maintain any internal state to keep track of the world.

2. **Accessible vs. inaccessible:**

If an agent's sensors give it access to the complete state of the environment needed to choose an action, the environment is accessible. An environment is effectively accessible if the sensors detect all aspects that are relevant to the choice of action. An accessible environment is convenient because the agent need not maintain any internal state to keep track of the world. Inaccessible environments are not implicitly non-deterministic.

3. **Deterministic vs. nondeterministic:**

If the next state of the environment is completely determined by the current state and the actions selected by the agents, then we say the environment is deterministic. In principle, an agent need not worry about uncertainty in an accessible, deterministic environment. If the environment is inaccessible, however, then it may appear to be non-deterministic. This is particularly true if the environment is complex, making it hard to keep track of all the inaccessible aspects. Thus, it is often better to think of an environment as deterministic or non-deterministic from the point of view of the agent.

4. **Episodic vs. sequential:**

In an episodic environment, the agent's experience is divided into "episodes". Each episode consists of the agent perceiving and then acting. The quality of its action depends just on the episode itself and does not depend on the actions in prior episodes. Episodic environments are much simpler because the agent does not need to think ahead.

5. **Discrete vs. continuous:**

This focuses on the way time is handled and to the percepts and actions of the agent. An environment is discrete if there are a limited number of distinct, clearly-defined states of the world which limits range of possible percepts and actions. Chess is discrete while taxi driving is continuous. Chess is discrete - there are a finite number of states and a discrete number of percepts and actions. Taxi driving is continuous - the speed and location of the taxi and the other vehicles sweep through a range of continuous values.

6. **Static vs. dynamic:**

A- Static environment:

An environment is static if it doesn't change between the time of perceiving and acting. Moreover, a static environment does not change while the agent is thinking. Static environments are easy to deal with it because the agent does not need to keep looking at the world while deciding on an action, nor need to worry about the passage of time. A static environment consists of unchanging surroundings in which an agent navigates, manipulates, or perhaps simply problem solves. In such an environment, there are no moving objects. Thus, the agent, then, does not need to adapt to new situations. Static environment includes one-player games, in which nothing changes through the action of the agent.

Negatives: The actual world is not at all static and the goal of AI projects is to create an agent that can navigate in the real world.

B- Dynamic environment:

If the environment can change while an agent is deliberating, then we say the environment is dynamic for the agent. (The environment is semidynamic if the environment itself does not change with the passage of time but the agent's performance score does). Dynamic environment changes over time independent of the actions of the agent. It can be unpredictable. This means that not only is the world changing but also it changes in a way that the agent cannot (fully) comprehend. This often occurs when an agent's representation of the world is incomplete (or non-existent). Because of this unpredictability, it may be desirable that the agent's processing be interruptible, to handle unexpected, and urgent, contingencies.

7. Simulated environments:

By operating in a simulated environment, architecture is able to avoid dealing with such issues as real-time performance and unreliable sensors. In simulated environment, the agent can be used to test higher-level cognitive functions such as planning and learning without real-world implementation issues. Operating in a simulated environment also offers the advantage that the agent may be exposed to a variety of different tasks and surroundings without an inordinate amount of development time. Thus, the same architecture can be applied to tasks involving space exploration and undersea diving without the necessity of developing the necessary hardware to transport the agent to either location. It has the ability to incrementally add new knowledge without significant slowdown.

Conclusion

In this chapter, we have aimed to give a general introduction to the field of artificial intelligence. Additionally, terms and concepts that have been used in this chapter will use frequently in next chapters when we will discuss agent concept and Dörner's approach (PSI-theory) that explained human action regulation through the relationships between cognition, emotion, and motivation. This chapter has highlighted key trends in the development of the field of artificial intelligence and its important goals and applications. The main framework of artificial intelligence field has been reviewed, many definitions have been stated and different points of view have been demonstrated. The main areas of artificial intelligence activity include expert systems, artificial neural networks, natural language understanding, computer vision, robotics and simulation have been discussed.

The reason for doing artificial intelligence is developing useful and smarter computer programs. However, the definitions of artificial intelligence were slightly different according to the author's point of view of the natural of artificial intelligence. The difference lies in two dimensions: one is focused on the thought processes and reasoning; another is involved with behaviour. Artificial intelligence can be viewed as an attempt to model aspects of human thought on computers but sometimes is defined as trying to solve by computer any problem that a human can solve faster. Our point of view is that artificial intelligence should not only model aspects of human thought, but also should have the same motives, emotions, and even though errors that humans have. Moreover, artificial intelligence should not build such intelligent program that is smarter than human; rather should construct intelligent program which has the same intelligence that humans have.

Chapter

3

Agents

Fundamentals, Types & Evaluation Criteria

Summary

The area of agents has been for at least the last ten years a constant growing area of interest. Agents are used as metaphors for work in most areas of the field of artificial intelligence. However, the word *agent* is currently in vogue in the popular computing press and within the artificial intelligence and computer science communities. This chapter clarifies with a brief overview the framework of the agent research. In section 3.1, we will provide a general agent description, definition and finally outline the characteristics and difficulties face agents. In section 3.2., basic fundamentals of building an intelligent agent will be discussed. Section 3.3 will briefly summarize the types of agents. Finally, in section 3.4, evaluation criteria of agents such as capabilities related to learning, planning, and robotic agent, interaction with environment and agent's performance will be demonstrated.

3.1 Introduction

3.1.1 Description of an agent:

The term agent covers a wide range of behaviour and functionality. In general, an agent is an active computational entity with a persistent identity that can perceive, reason about, and initiate activities in its environment that can communicate (with other agents). An (*intelligent*) agent perceives its environment with sensors and acts (*rationally*) upon that environment with its effectors. Moreover, an agent is a computer software system whose perceives and acts in an environment to achieve specific goals. We can split an agent into an architecture and an agent program, which maps the percepts to some actions (Niederberger & Gross, 2002, p.33) and the difference between an agent and a program is that all software agents are programs, but not all programs are agents (Franklin & Graesser, 1997).

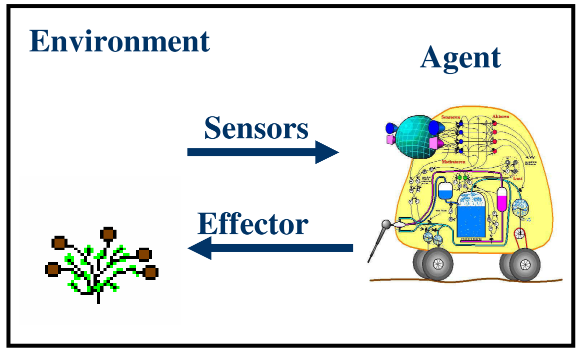

Figure 3.1: An agent and environment.

In summary, an agent is something that perceives and acts in its environment based upon the perceived information (ibid, p.33).

An agent = architecture + program.

Figure 3.2: An agent formula.

Source: (Russell & Norving, 1995, p.36).

3.1.2 Agent definitions:

There are various definitions of the term "*agent*", and these definitions range from the simple to the lengthy. Therefore, from our point of view, a review of simple definitions with supplemental characteristics and explanations of agent could solve the definition problem.

Erickson's definition:

An agent is a program that is, to some degree, capable of initiating actions, forming its own goals, constructing plans of action, communicating with other agents, and responding appropriately to events without being directly controlled by a human (Erickson, 1997, p.80).

Russell and Norvig's definition:

An agent is anything that can be viewed as perceiving its environment through sensors and acting upon that environment through effectors (Russell & Norving, 1995).

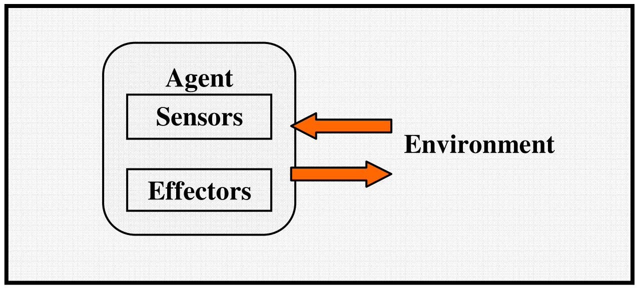

Figure 3.3: Russell & Norvig's definition.

Maes's definition:

Agents are computational systems that inhabit some complex dynamic environment, sense and act autonomously in this environment, and by doing so realize a set of goals or tasks for which they were designed (Maes, 1995).

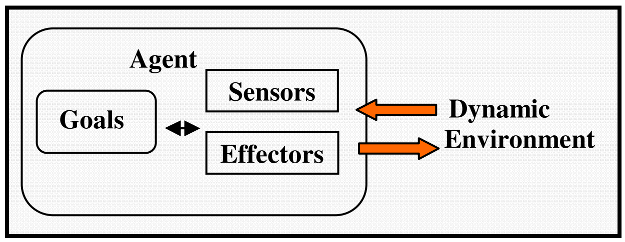

Figure 3.4: Maes's definition.

Hayes-Roth's definition:

Intelligent agents continuously perform three functions: perception of dynamic conditions in the environment; action to affect conditions in the environment; and reasoning to interpret perceptions, solve problems, draw inferences, and determine actions (Hayes-Roth , 1995).

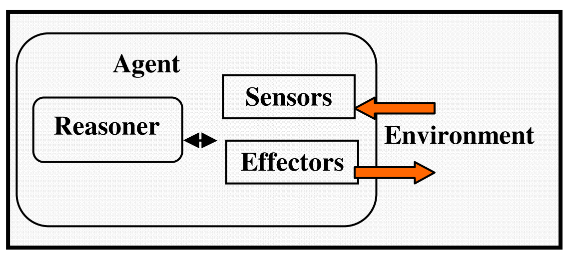

Figure 3.5: Hayes-Roth's definition.

Franklin and Graesser's definition:

An autonomous agent is a system situated within and a part of an environment that senses that environment and acts on it over time, in pursuit of its own agenda and so as to effect what it senses in the future (Franklin & Graesser, 1997).

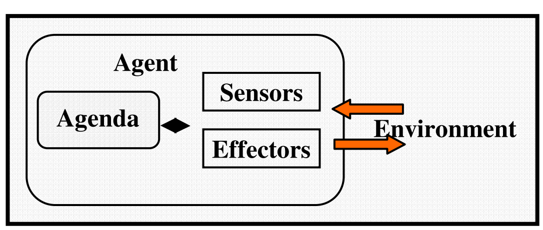

Figure 3.6:
Franklin and Graesser's definition.

Comment

Despite the big efforts spent on research in the area, there is no agreement about what should be meant by an agent. However, there are four agreements among researchers. Firstly, all agents are situated in some environment. Secondly, each senses its environment and act autonomously upon it. Thirdly, no other entity is required to feed it input, or to interpret and use its output and no agent exists without a context. And finally, every agent, if correct, meets its design objectives. Each acts so that its current actions may effect its later sensing, that is its actions effect its environment. Moreover, each acts continually over some period of time.

Hence, some researchers seem to have given up the attempts to define agents and characterize basically everything as agents. Obviously, Russell and Norvig's definition depends on what we presume as the environment, and on what sensing and acting mean. If we define the environment as whatever provides input and receives output, and take receiving input to be sensing and producing output to be acting, every program is an agent.

According to Maes's definition, "autonomously" as a character of agent is added and environments are restricted to being complex and dynamic. Therefore, her definition considers agent as complex information processing system. However, the definition is quite open to extension and interpretation. Hayes-Roth's definition claims that agents reason during the process of action selection. According to Franklin and Grasser's definition, "sense in the future" is too open for interpretation for the definition to be objective and it is much less formal.

3.1.3 Characteristics of an agent:

In addition, an agent is computer program that is characterized by carrying out some set of operations and can demonstrate some degree of independence or autonomy. It should have sensors to perceive conditions in its environment, and have ability to affect conditions in the environment. It should have reasoning to interpret perceptions, solve problems, respond in a meaningful way, and determine actions. Moreover, it should continuously realize a set of goals or tasks and have its own ideas about how to accomplish tasks. It has the ability to take over some human tasks and interact with people in human like ways, and makes a decision about what action to perform based on its experience. Agents consider dynamic when they can exercise some degree of activity. An agent must have its own unique identity.

In principle, an agent program mainly consists of the following tasks which are executed repeatedly (Niederberger & Gross, 2002, p.33):

1. **Perception**: The agent gets actual information from its environment to sense its new situation after the last action.
2. **Inference**: The agent infers with respect to its percepts about the world and what has to be done.
3. **Selection**: The agent selects one or more actions considering the possible outcomings of step 2.
4. **Acting**: The selected action is performed.

Furthermore, an intelligent agent interacts with–influences and is influenced by–other dynamic entities in its environment. It perceives data from the environment, reasons to interpret perceptions, solve problems, make decisions, etc., acts to affect external entities and to achieve its goals. To keep pace with external events and avoid missing important demands and opportunities for action, the agent performs these functions asynchronously, concurrently, and selectively. Nonetheless, these functions must be integrated. Perception must inform reasoning and action. Reasoning must guide perception and action. Action must feed back on perception and reasoning (Hayes-Roth, 1991, p.79).

In addition, an intelligent agent acts as a single purposeful entity. It attempts to construct a consistent interpretation of the world, acquire information relevant to its ongoing activities, notice important unanticipated events, and take actions that advance its goals. It establishes and modifies its own goals and allocates its own limited resources among competing tasks in a purposeful, coordinated manner, in accordance with its current goals and constraints and its current interpretation of the environment (ibid).

3.1.4 Difficulties challenge intelligent agents:

1. Uncertainty in the World Model:

The agent can never be completely certain about the state of the external world since there is ambiguity and uncertainty that may happen because of the following difficulties: First, sensors have limited precision and accuracy. Second, there are hidden variables that sensors can't "see", e.g. vehicle behind large truck or storm clouds approaching. Finally, the future is unknown, uncertain (i.e., cannot foresee all possible future events which may happen).

2. Construct new architecture or reuse an existing architecture?

Researchers attempting to develop new agents are faced with a difficult problem: should they construct their own symbolic architecture for the tasks at hand, or should they reuse an existing architecture? Because symbolic architectures tend to be large and complex, development requires a significant amount of time and effort (Wallace & Laird, 1999, p.117).

3.2 Basic Fundamentals of Building an Intelligent Agent

3.2.1 Introduction:

This section will discuss the basic terminology of general agent architecture. According to Niederberger and Gross (2002, p.57), designing an agent architecture is a non-trivial task. Considerations have to be taken with respect to a large number of requirements and constraints. For example, to build an agent we need to answer the following questions:

- What is the goal to be achieved? The answer of this question describes a situation we want to achieve, a set of properties that we want to hold, etc.

- What are the actions? The answer of this question characterizes the primitive actions or events that are available for making changes in the world in order to achieve a goal. The given action should specify whether that action can be applied to the current world (i.e., is it applicable and legal), and what the exact state of the world will be after the action is performed in the current world. The number of actions / operators depends on the representation used in describing a state. What relevant information is necessary to encode about the world to describe the state of the world, describe the available transitions, and solve the problem?

3.2.2 Perception and situation assessment:

Sensing and perception can be thought to be two different things. Sensing is the action of getting a stimulus while perception decides what it is and what the further meaning of this stimulus can be. Once the stimulus has been sensed, it can be perceived which is principally a classification problem (Niederberger & Gross, 2002, p. 42). Moreover, perception considers inputs from the environment, such as the location of a fire and an indication of its intensity. The agent may also obtain information about the environment through sensing actions (Winikoff et al, 2001).

An agent may sense the world through different modalities, just as a human has access to sight, hearing, and touch. The sensors may range from simple devices to more complex mechanisms. Perception can also involve the integration of results from different modalities into a single assessment or description of the environmental situation, which an architecture can represent for utilization by other cognitive processes. Perception is a broad term that covers many types of processing, from inexpensive ones that an architecture can support automatically to ones that require limited resources and so must be invoked through conscious intentions. For example, the human visual system can detect motion in the periphery without special effort, but the fovea can extract details only from the small region at which it is pointed. A cognitive architecture that includes the second form of sensor must confront the issue of attention that is deciding how to allocate and direct its limited perceptual resources to detect relevant information in a complex environment. An architecture that supports perception should also deal with the issue that sensors are often noisy and provide at most an inaccurate and partial picture of the agent's surroundings. Dynamic environments further complicate matters in that the agent must track changes that sometimes occur at a rapid rate.

An architecture can also acquire and improve this knowledge by learning from previous perceptual experiences. An intelligent agent should also be able to move beyond perception of isolated objects and events to understand and interpret the broader environmental situation. Thus, situation assessment requires an intelligent agent to combine perceptual information about many entities and events, possibly obtained from many sources, to compose a large-scale model of the current environment (Langley& Laird, 2002, pp.7-8).

3.2.3 Recognition and categorization:

An agent's filter override mechanism must be carefully designed to embody the right degree of sensitivity to the problems and opportunities that arise in her environment. If the agent is overly sensitive, willing to reconsider her plans in response to every unanticipated event, then her plans will not serve sufficiently to limit the number of options about which she must deliberate. On the other hand, if the agent is not sensitive enough, she will fail to react to significant deviations from her expectations (Bratman et al, 1988).

Moreover, an intelligent agent must make some contact between its environment and its knowledge. This requires the ability to recognize situations or events as instances of known or familiar patterns. However, recognition need not be limited to static situations. Recognition is closely related to categorization, which involves the assignment of objects, situations, and events to known concepts or categories. To support recognition and categorization, a cognitive architecture must provide some way to represent patterns and situations in memory. Because these patterns must apply to similar but distinct situations, they must encode general relations that hold across these situations. An architecture must also include some recognition process that lets it identify when a particular situation matches a stored pattern or category and, possibly, measure the degree to which it matches. Finally, an ideal architecture should include some means to learn new patterns or categories from instruction or experience and to refine existing patterns when appropriate (Langley& Laird, 2002, p. 6).

3.2.4 Belief, desire and intention:

- **Beliefs:** A belief is some aspect of the agent's knowledge or information about the environment, self or other agents; (informative). For example an agent might believe there is a fire at (X) because she saw it recently, even if she cannot see it now. Beliefs are essential since an agent has limited sensory ability and also it needs to build up its knowledge of the world over time (Winikoff et al, 2001).

- **Desires:** Desires are understood to be things the agent wants to achieve. In decision-theoretic accounts, an agent is seen as selecting a course of action on the basis of her subjective expected utility, which is a function of the agent's beliefs and desires (Bratman et al, 1988).

- **Intention:** Intentions are defined as the currently chosen course of action; *deliberative* (Winikoff et al, 2001).

Cohen and Levesque (through: Wooldridge& Jennings, 1995) identify seven properties that must be satisfied by a reasonable theory of intention: **1.** Intentions pose problems for agents, who need to determine ways of achieving them. **2.** Intentions provide a 'filter' for adopting other intentions, which must not conflict. **3.** Agents track the success of their intentions, and are inclined to try again if their attempts fail. **4.** Agents believe their intentions are possible. **5.** Agents do not believe they will not bring about their intentions. **6.** Under certain circumstances, agents believe they will bring about their intentions. **7.** Agents need not intend all the expected side effects of their intentions.

Table 3.1: Properties of Intention.

3.2.5 Reasoning:

Problem solving is closely related to reasoning. In fact, reasoning is a central cognitive activity that lets an agent augment its knowledge state. Whereas planning is concerned primarily with achieving objectives in the world by taking actions, reasoning draws mental conclusions from other beliefs or assumptions that the agent already holds. For example, a pilot might conclude that, if another plane changes its course to intersect his own, it is probably an enemy fighter. To support such reasoning, a cognitive architecture must first be able to represent relationships among beliefs. Reasoning plays an important role not only when inferring new beliefs but when deciding whether to maintain existing ones. To the extent that certain beliefs depend on others, an agent should track the latter to determine whether it should continue to believe the former, abandon it, or otherwise alter its confidence. Such belief maintenance is especially important for dynamic environments in which situations may change in unexpected ways, with implications for the agent's behaviour. One general response to this issue involves maintaining dependency structures in memory that connect beliefs and that the architecture can use to propagate changes as they occur (Langley& Laird, 2002,pp. 10-11).

3.2.6 Planning:

For many years, planning had a quite specific meaning in AI. It was the process of formulating a program of action to achieve some specified goal (Pollack, 1992). Plans are means of achieving certain future world states. In addition plan is a way of realising a goal (Winikoff et al, 2001). A plan for achieving a goal provides a function which returns the next action to be performed. This function takes into account the current state of the world (beliefs), what actions have already been performed, and might involve sub-goals and further plans. Intuitively, plans are an abstract specification of both the means for achieving certain desires and the options available to the agent (ibid). An agent has a simple plan if and only if she believes that all the acts in that plan play a role in it by generating another act (Pollack, 1990, p.89).

Winikoff et al (2001) argued that each plan has:

1. A body describing the primitive actions or sub-goals that have to be achieved for plan execution to be successful;
2. An invocation condition which specifies the triggering event, and
3. A context condition which specifies the situation in which the plan is applicable.

In addition, there are two mainly types of planning, hierarchical and conditional planning (Russell & Norving, 1995). *Hierarchical planning* is an approach to decomposing the planning into multiple levels of abstraction. At a higher level, a planner may find a sequence of places to go, while at a lower level, concrete movement instructions for the effectors of the agent must be found. Resolving the plan directly at the lower level would produce a much longer plan. At the lowest level, primitive operators complete the plan which can be executed directly by the agent. *Conditional Planning* deals with incomplete information by constructing a conditional plan that accounts for each possible situation. The agent finds out which part of the plan to execute by including its sensory information in the plan to test for the appropriate conditions. The major disadvantage of conditional planning is the big number of possible conditions, which grows exponentially with the number of steps in the plan. Another approach with incomplete or incorrect information is *execution monitoring*. Here, the agent monitors what is happening and can therefore decide on what is going on and when things went wrong. In this case, a *re-planning* has to be done to find a new plan from the unexpected situation.

Pollack (1990) summarized the analysis of having a plan as follows:

An agent "A" has a plan to do "β" that consists in doing some set of acts "II" provided that:

1. "A" believes that he can execute each act in "II".
2. "A" believes that executing the acts in "II" will entail the performance of "β".
3. "A" believes that each act in "II" plays a role in his plan.
4. "A" intends to execute each act in "II".
5. "A" intends to execute "II" as a way of doing "β".
6. "A" intends each act in "II" to play a role in his plan

Intelligent agents that operate in and monitor dynamic environments must often modify existing plans in response to unanticipated changes. This can occur in several contexts. For instance, an agent should update its plan when it detects a changed situation that makes some planned activities inapplicable, and thus requires other actions. Another context occurs when a new situation suggests some more desirable way of accomplishing the agent's goal; such opportunistic planning can take advantage of these unexpected changes. Monitoring a plan's execution can also lead to revised estimates about the plan's effectiveness, and ultimately to a decision to pursue some other course of action with greater potential. Re-planning can draw on the same mechanisms as generating a plan from scratch, but requires additional operators for removing actions or replacing them with other steps. Similar methods can also adapt to the current situation a known plan the agent has retrieved from memory (Langley& Laird, 2002, pp.9-10).

3.2.7 Decision making and choice:

The essence of intelligent agents is rational decision making. An important aspect in decision making is balancing proactive and reactive aspects. On the one hand we want the agent to stick with its goals by default; on the other hand we want it to take changes in the environment into account (Winikoff et al, 2001).

In other words, to operate in an environment, an intelligent system requires the ability to make decisions and select among alternatives. To support decision making, a cognitive architecture must provide some way to represent alternative choices or actions, whether these are internal cognitive operations or external ones. It must also offer some process for selecting among these alternatives, which most architectures separate into two steps:

The first determines whether a given choice or action is allowable, typically by associating it with some pattern and considering it only if the pattern is matched. For instance, one can specify the conditions under which a chess move is legal, then consider that move only when the conditions are met.

The second step selects among allowable alternatives, often by computing some numeric score and choosing one or more with better scores. Finally, an ideal cognitive architecture should incorporate some way to improve its decisions through learning (Langley& Laird, 2002).

3.2.8 Prediction and monitoring:

Cognitive architectures exist over time, which means they can benefit from an ability to predict future situations and events accurately. For example, a good driver knows approximately when his car will run out of gas. Perfect prediction may not be possible in many situations, but perfection is seldom necessary to make predictions that are useful to an intelligent system. Prediction requires some model of the environment and the effect actions have on it, and the architecture must somehow represent this model in memory.

One general approach involves storing some mapping from a description of the current situation and an action onto a description of the resulting situation. Another instead encodes the effects of actions or events in terms of changes to the environment. In either case, the architecture also requires some mechanism that uses these knowledge structures to predict future situations, say by recognizing a class of situations in which an action will have certain effects. An ideal architecture should also include the ability to learn predictive models from experience and to refine them over time. Once an architecture has a mechanism for making predictions, it can utilize those predictions to monitor the environment. Because monitoring relates sensing to prediction, it raises issues of attentional focus when an architecture has limited perceptual resources. Monitoring also supports learning, since errors in prediction can help an agent improve its model of the environment (ibid, p. 8).

3.2.9 Execution, action and control:

Based on its perception, the agent has to choose an action which it is going to execute (Niederberger & Gross, 2002, p.42). There are a number of questions which intelligent agents must answer, such as: *Which* action shall I perform now? *Which* goal do I work on now? *How* shall I attempt to realise this goal? *Where* shall I go now (for mobile agents)? And *who* shall I interact with (for social agents)? Mechanisms to answer these kinds of questions are core intelligent agent processes. (Winikoff et al, 2001).

Cognition occurs to support and drive activity in the environment. To this end, a cognitive architecture must be able to represent and store motor skills that enable such activity. For example, a mobile ground robot or unmanned air vehicle should have skills or policies for navigating from one place to another, for manipulating its surroundings with effectors, and for coordinating its behaviour with other agents on its team. These may be encoded solely in terms of primitive or component actions, but they may also specify more complex multi-step skills or procedures. The latter may take the form of plans that the agent has generated or retrieved from memory, especially in architectures that have grown out of work on problem solving and planning. However, other formulations of motor skill execution, such as closed-loop controllers, have also been explored.

A cognitive architecture must also be able to execute skills and actions in the environment. In some frameworks, this happens in a completely reactive manner, with the agent selecting one or more primitive actions on each decision cycle, executing them, and repeating the process on the next cycle. This approach is associated with closed-loop strategies for execution, since the agent can also sense the environment on each time step. The utilization of more complex skills supports open- loop execution, in which the agent calls upon a stored procedure across many cycles without checking the environment. However, a flexible architecture should support the entire continuum from fully reactive, closed-loop behaviour to automatized, open-loop behaviour, as can humans.

Ideally, a cognitive architecture should also be able learn about skills and execution policies from instruction and experience. Such learning can take different forms, many of which parallel those that arise in planning and problem solving. For example, an agent can learn by observing another agent's behaviour, by successfully achieving its goals, and from delayed reward signals. Similarly, it can learn or refine its knowledge for selecting primitive actions, either in terms of heuristic conditions on their application or as a numeric evaluation function that reflects their utility. Alternatively, an agent can acquire or revise complex skills in terms of known skills or actions (Langley& Laird, 2002, p.11).

Comment

A traditional argument for both psychology and artificial intelligence addresses components and mechanisms for such an intelligent agent, in which the problems of intelligence are to transform perception into a useful mental representation; apply a cognitive process to create a representation of desired actions. Moreover, cognitive psychology considers psychic processes (i.e., thinking, learning, and memory-processes, as processes of information processing). There are a lot of theoretical systems which describe human thought as information processing. However, how could one describe motivation and emotion in terms of information processing? The answer of the previous question, and a variety of factors and features that will be important to consider when building robots that are meant to act autonomously, will be described in chapter four when we demonstrate Dörner's approach (PSI-theory). Briefly, Dörner is interested in action regulation of human being, in which man is considered not only a cognitive system in the sense of contemporary cognitive science, but also a motivated emotional-cognitive system.

3.2.10 Interaction and communication:

Sometimes the most effective way for an agent to obtain knowledge is from another agent, making communication another important ability that an architecture should support. A communicating agent must represent the knowledge that it aims to convey or that it believes another agent intends for it. The content so transferred can involve any of the cognitive activities that have been discussed so far. Thus, two agents can communicate about categories recognized and decisions made, about perceptions and actions, about predictions and anomalies, and about plans and inferences. A cognitive architecture should also support mechanisms for transforming knowledge into the form and medium through which it will be communicated. The most common form is spoken or written language, which follows established conventions for semantics, syntax, and pragmatics onto which an agent must map the content it wants to convey. Generation of language can be viewed as a form of planning and execution, whereas understanding of language can be viewed as a form of perception and inference. However, the specialized nature of natural language makes these views misleading, since the task raises many additional issues.

An important form of communication occurs in conversational dialogues, which require both generation and understanding of natural language, as well as coordination with the other agent in the form of turn taking. Learning is also an important issue in language and other forms of communication, and some communicative tasks, like question answering, require access to memory for past events and cognitive activities (Langley& Laird, 2002, pp.11-12).

3.2.11 Memory, learning and self-reflection:

A cognitive architecture can also benefit from capabilities that cut across those described in the previous sections, in that they operate on mental structures produced or utilized by them. One capacity of this sort involves remembering - the ability to encode and store the results of cognitive processing in memory and to retrieve or access them later. An agent cannot remember external situations or its own physical actions; it can only recall cognitive structures that describe those events or inferences about them. This idea extends naturally to memories of problem solving, reasoning, and communication. To support remembering about any cognitive activity, the architecture must store the cognitive structures generated during that activity, index them in memory, and retrieve them when needed. The resulting structures are often referred to as episodic memory (ibid, pp.11-12).

Another capability that requires access to traces of cognitive activity is reflection. This may involve processing of either recent mental structures that are still available or older structures that the agent must retrieve from episodic memory. One type of reflective activity concerns the justification or explanation of an agent's inferences, plans, decisions, or actions in terms of cognitive steps that led to them. Another revolves around meta-reasoning about other cognitive activities, which an architecture can apply to the same areas as explanation, but which emphasizes their generation (e.g., forming inferences or making plans) rather than their justification. To the extent that reflective processes lay down their own cognitive traces, they may themselves be subject to reflection. However, an architecture can also support reflection through less transparent mechanisms, such as statistical analyses, that are not themselves inspectable by the agent.

A final important ability that applies to many cognitive activities is learning. It has been discussed previously the various forms this can take, in the context of different architectural capacities, but we should also consider broader issues. Unlike the storage of cognitive structures in episodic memory, learning involves generalization beyond specific beliefs and events. Although most architectures carry out this generalization at storage time and enter generalized knowledge structures in memory, it can instead happen at retrieval time through analogical or case-based reasoning. Either approach can lead to different degrees of generalization or transfer, ranging from very similar tasks, to other tasks within the same domain, and even to tasks within related but distinct domains (Langley& Laird, 2002, pp.11-12).

Many architectures treat learning as an automatic process that is not subject to inspection or conscious control, but one can also use meta-reasoning to support learning in a more deliberate manner. The data on which learning operates may come from many sources, including observation of another agent, an agent's own problem solving behaviour, or practice of known skills. But whatever the source of experience, all involve processing of memory structures to improve the agent's capabilities (ibid, pp. 12-13).

3.3 Types of Agents

3.3.1 Introduction:

There are several dimensions to classify agents. Firstly, agents may be classified by their mobility (i.e., by their ability to move around some network). Secondly, they may be classed or ranked from least to most complex as either deliberative (goal-based agents and utility-based agents) or reactive (simple reflexive agents and reflexive agents with internal state). Deliberative agents possess an internal symbolic reasoning model, and they engage in planning and negotiation with other agents in order to achieve their goals. On other hand, reactive agents do not have any internal symbolic models of their environment, and they act using "a stimulus– response" type of behaviour by responding to the present state of the environment in which they are embedded. Thirdly, agents may be classified along several attributes which ideally they should exhibit such as; autonomy, learning and co-operation. For example, learning agent learns action policies from previous encounters with similar situations, and these policies become increasingly accurate as experience accumulates.

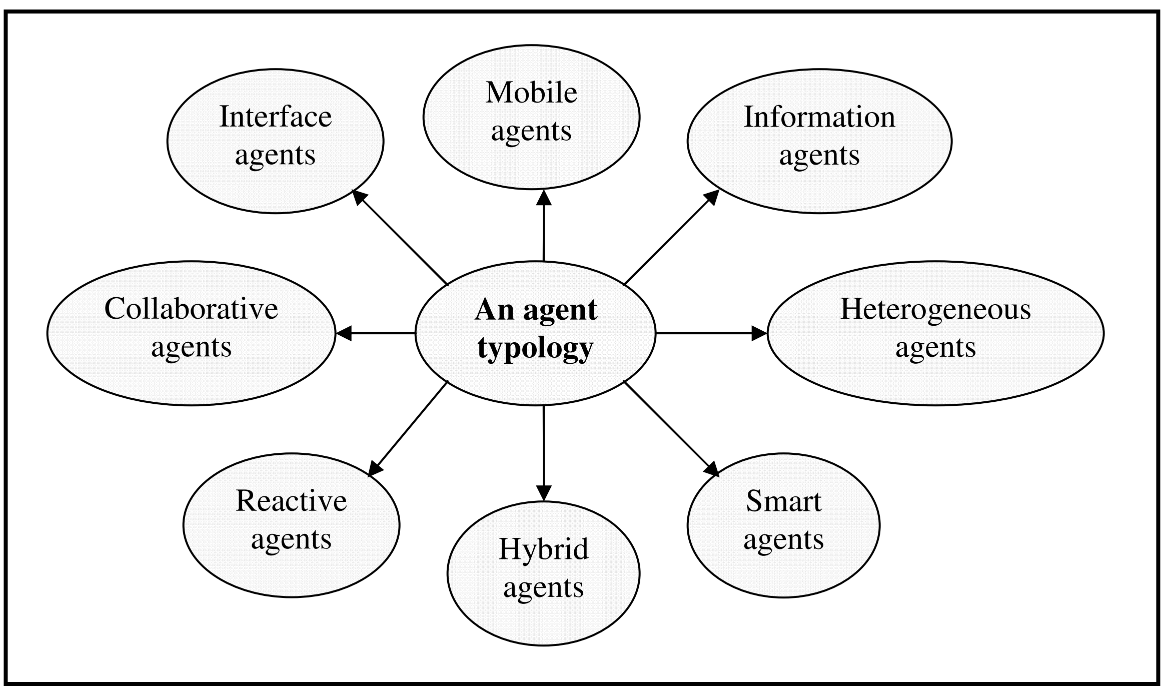

Figure 3.7: A classification of software agents.

Source: (Nwana, 1996).

Nwana (1996) introduced eight major categories of agent as shown in figure 3.7:

1. **Collaborative agents:** Collaborative Agents emphasize autonomy and cooperation (with other agents) in order to perform tasks for their owners. They may learn, but this aspect is not typically a major emphasis of their operation. In order to have a coordinated set up of collaborative agents, they may have to *negotiate* in order to reach mutually acceptable agreements on some matters.
2. **Interface agents:** Interface Agents emphasize autonomy and learning in order to perform tasks for their owners. They support and provide assistance, typically to a user learning to use a particular application such as a spreadsheet or an operating system. The user's agent observes and monitors the actions taken by the user in the interface (i.e., 'watches over the shoulder of its user'), learns new 'shortcuts', and suggests better ways of doing the task.
3. **Mobile agents:** Mobile agents are computational software processes capable of roaming wide area networks such as the WWW*, interacting with foreign hosts, gathering information on behalf of its owner and coming 'back home' having performed the duties set by its user.
4. **Information agents:** In short, Information agents perform the role of managing, manipulating or collating information from many distributed sources.
5. **Reactive agents:** In sections 3.3.2 and 3.3.3., reactive agents will be discussed.
6. **Hybrid agents:** Hybrid agents refer to those whose constitution is a combination of two or more agent *philosophies* within a singular agent. These philosophies include a mobile philosophy, an interface agent philosophy, collaborative agent philosophy, etc.
7. **Heterogeneous agents:** Heterogeneous agent systems, unlike hybrid systems, refer to an integrated set-up of at least two or more agents which belong to two or more different agent classes. A heterogeneous agent system may also contain one or more hybrid agents.
8. **Smart agents.**

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* For further details about agents' applications and internet see (Maes, 1997).

Types of reactive and deliberative agents will be shortly shown:

3.3.2 Simple reflex agent:

Description:

Simple reflex agents (also called stimulus-response agents) just react to the current situation at each time step with no memory of past actions or situations. In other words, it responds immediately to its percepts (Niederberger & Gross, 2002, p.34). This type of agent is generally very responsive because, without contextual information, the proper reaction to the current situation can be calculated very quickly (Laird & van Lent, 1999, p.579). The decision is based on so called *condition-action rules*, which are simple if-then relations. Humans have many such reflexes, for example closing the eyes when something is approaching them. The whole knowledge of the agent is then encoded into these rules (see: Niederberger & Gross, 2002, p.34). Stimulus-response agents can also implement multiple behaviours but aren't easily able to represent higher level tactics (Laird & van Lent, 1999, p.579). Figure (3.8) and table (3.2) give the structure of a simple reflex agent in schematic form, showing how the condition–action rules allow the agent to make the connection from percept to action.

Limitations:

Simple-reflex-agents use simple if-then rules match percepts to actions, and respond immediately to percepts (Niederberger & Gross, 2002, p.33). No need to consider all percepts, and it can generalize percepts by mapping to the same action. Moreover, it could adapt to changes in the environment by adding rules. Although such agents can be implemented very efficiently, their range of applicability is very narrow. Even for very simple environments, the need for an internal state arises to keep track of specific information, when the complete access to the environment is not guaranteed (ibid, p.34).

The following problems could be found in such architecture:

1. May be too big to generate and store.
2. Not adaptive to changes in the environment; instead entire table must be updated if changes occur.
3. No knowledge of non-perceptual parts of the current state.
4. Reacts only to current percept.
5. No history remembered.

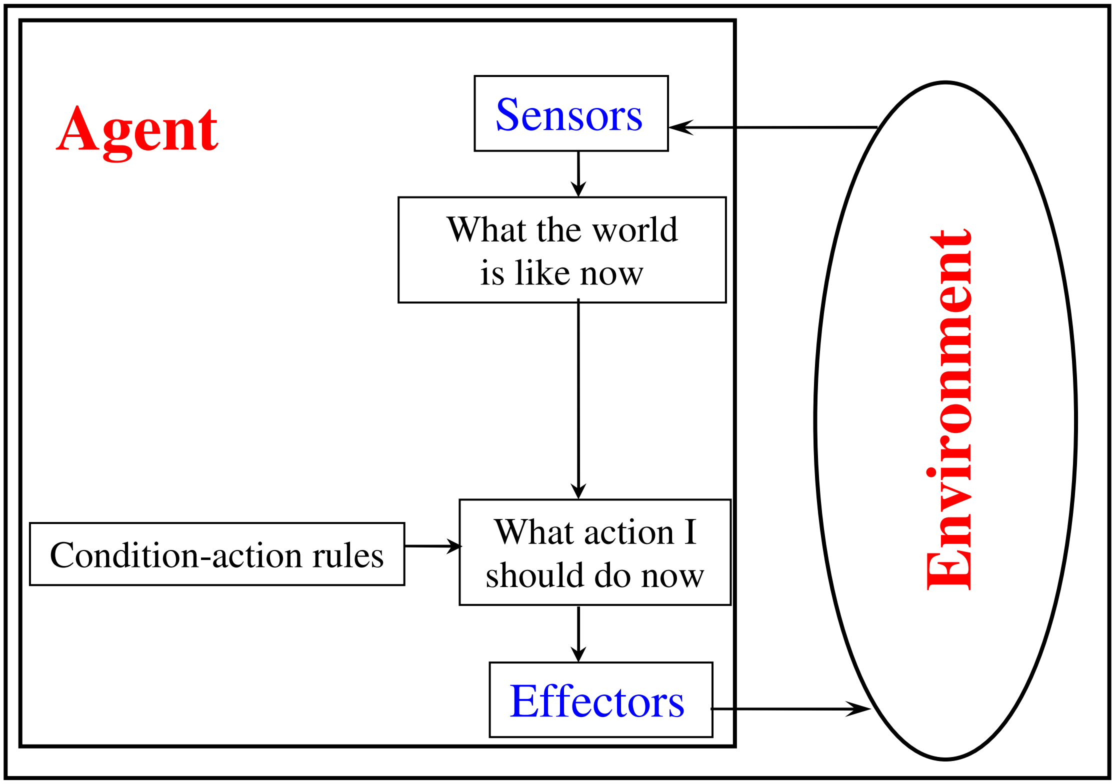

Figure 3.8: Schematic diagram of a simple reflex agent.

Source: (Russell & Norving, 1995, p.41).

function Simple-Reflex-Agent (percept) **returns** action
static: rules, a set of condition-action rules
state - Interpret-Input (percept)
rule - Rule-Match (state, rules)
action - Rule-Action (rule)

Table 3.2: A simple reflex agent.

It works by finding a rule whose condition matches the current situation (as defined by the percept) and then doing the action associated with that rule (ibid, p.41).

3.3.3 Reflex agent with an internal state:

Description:

The simple reflex agent described before will work only if the correct decision can be made on the basis of the current percept. Unfortunately, in some cases, the agent may need to maintain some internal state information in order to distinguish between world states that generate the same perceptual input but nonetheless are significantly different. Here, "significantly different" means that different actions are appropriate in the two states. Updating this internal state information as time goes by requires two kinds of knowledge to be encoded in the agent program. First, we need some information about how the world evolves independently of the agent. Second, we need some information about how the agent's own actions affect the world. Figure (3.9) gives the structure of the reflex agent, showing how the current percept is combined with the old internal state to generate the updated description of the current state. Table (3.3) shows the agent program. The interesting part is the function "update-state", which is responsible for creating the new internal state description.

3.3.4 Goal-based agents:

Description:

Knowing about the current state of the environment is not always enough to decide what to do. In other words, the agent needs some sort of goal information, which describes situations that are desirable. The agent program can combine this with information about the results of possible actions (the same information as was used to update internal state in the reflex agent) in order to choose actions that achieve the goal. Sometimes this will be simple, when goal satisfaction results immediately from a single action. Moreover, decision–making of this kind is fundamentally different from the condition–action rules, in that it involves consideration of the future—both "What will happen if I do such-and-such?" and "Will that make me happy?" Figure (3.10) and table (3.4) show the goal-based agent's structure.

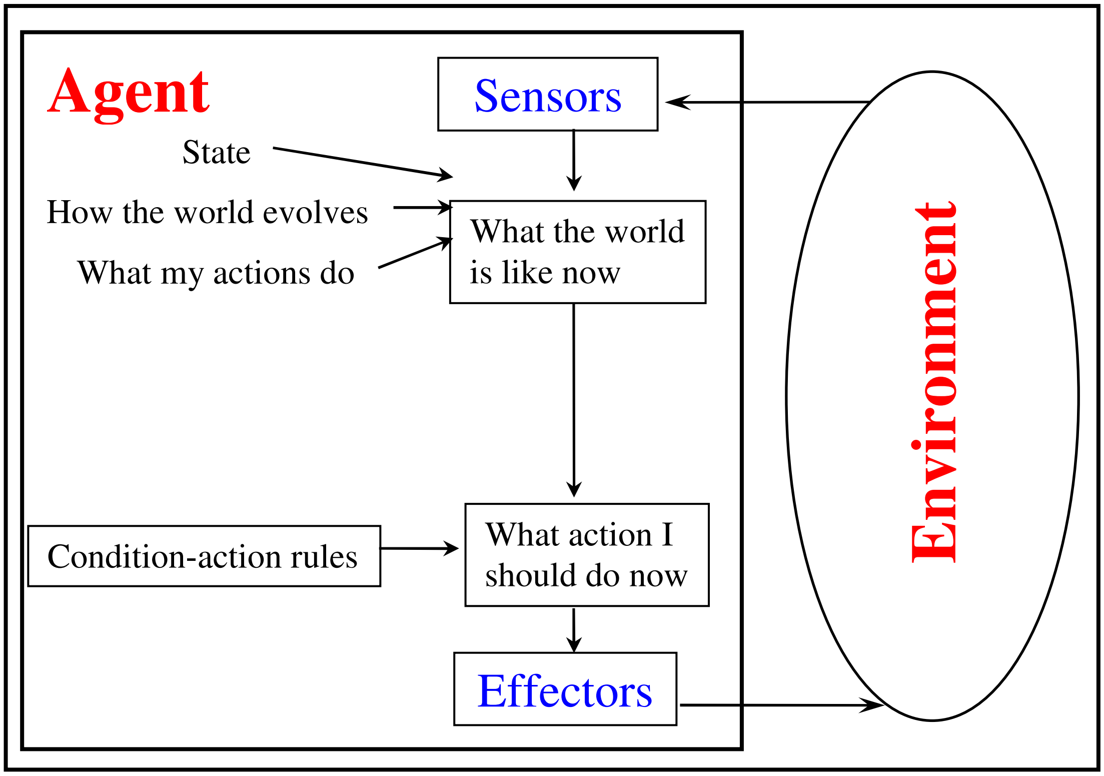

Figure 3.9: A reflex agent with internal state.

Source: (Russell & Norving, 1995, p.43).

function Reflex-Agent-With-State (percept) **returns** action
static: state, a description of the current world state
rules, a set of condition-action rules
state - UpDate-State (state, percept)
rule - Rule-Match (state, rules)
action - Rule-Action (rule)
state - UpDate-State (state, action)

Table 3.3: A reflex agent with internal state. It works by finding a rule whose condition matches the current situation (as defined by the percept and the stored internal state) and then doing the action associated with that rule (ibid, p.43).

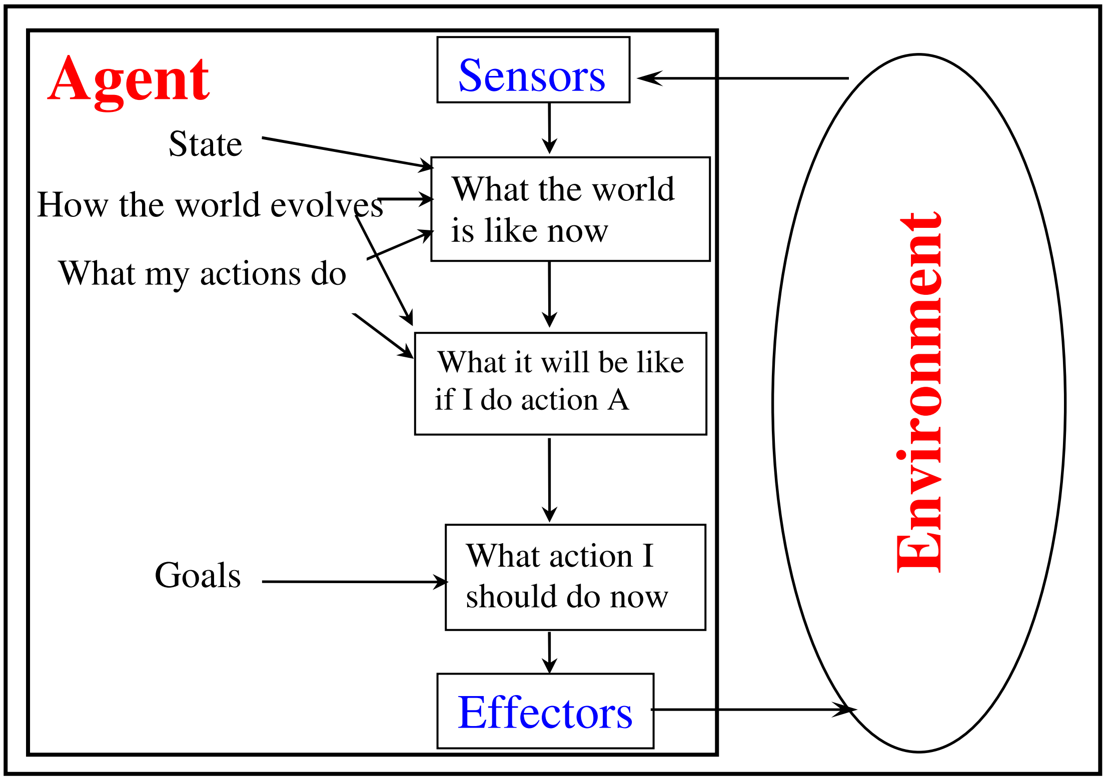

Figure 3.10: An agent with explicit goals.

Source: (Russell & Norving, 1995, p.44).

function Reflex-Agent-With-State-And-Goals (percept) returns action

static: state, a description of the current world state

rules, a set of condition-action rules

goals, a set of goals

state - UpDate-State (state, percept)

rule - Rule-Match (state, rules, goal)

action - Rule-Action (rule)

state - UpDate-State (state, action)

return action

Table 3.4: Goal-based agent. Actions chosen to achieve a desired situation and goals help decide which situations are good.

Limitations:

Although the goal-based agent appears less efficient, it is more flexible with respect to reaching different destinations. Moreover, goal-based agents may have to consider long sequences of possible actions before deciding if goal is achieved.

3.3.5 Utility-based agents:

Description:

Goals alone are not really enough to generate high-quality behaviour because of, for example, many action sequences that should be taken. Goals just provide a crude distinction between “happy” and “unhappy” states, whereas a more general performance measure should allow a comparison of different world states (or sequences of states) according to exactly how happy they would make the agent if they could be achieved. Because “happy” does not sound very scientific, the customary terminology is to say that if one world state is preferred to another, then it has higher utility for the agent utility is therefore a function that maps a state onto a real number, which describes the associated degree of happiness.

Limitations:

A complete specification of the utility function allows rational decisions in two kinds of cases where goals have trouble. Firstly, when there are conflicting goals, only some of which can be achieved (for example, speed and safety), the utility function specifies the appropriate trade-off. Secondly, when there are several goals that the agent can aim for, none of which can be achieved with certainty, utility provides a way in which the likelihood of success can be weighed up against the importance of the goals. The overall utility-based agent structure appears in Figure (3.11) and table (3.5).

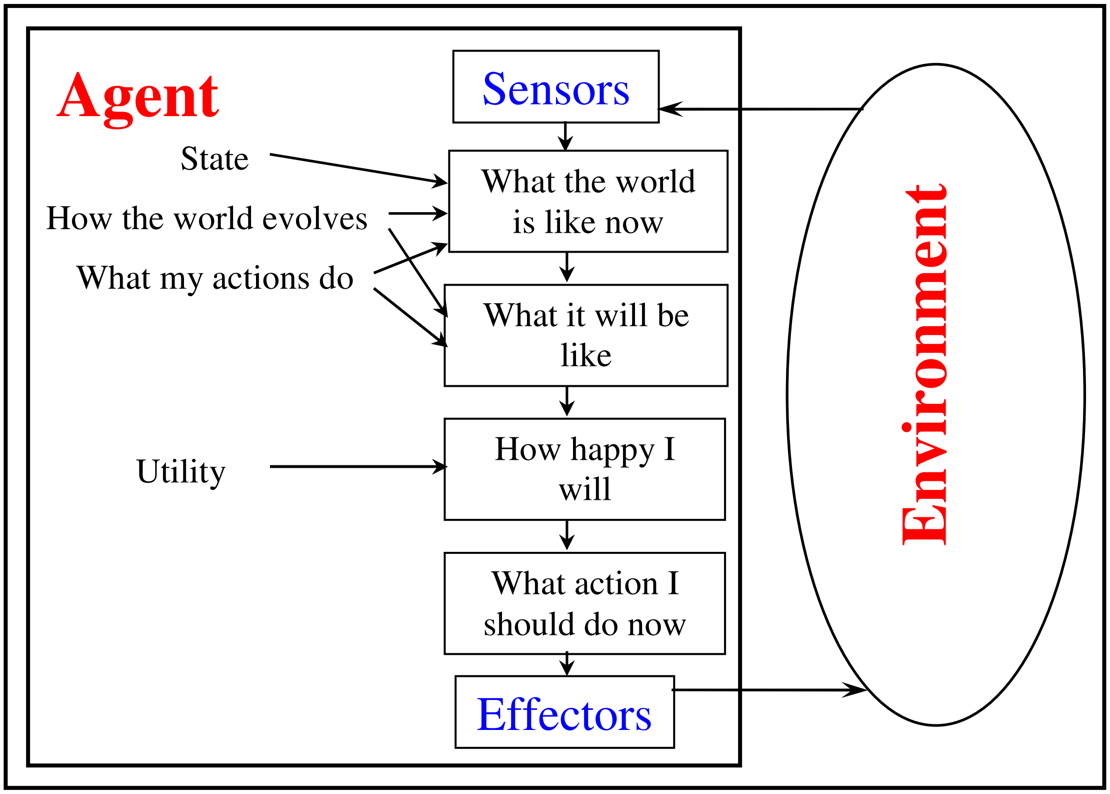

Figure 3.11: A complete utility-based agent.

Source: (Russell & Norving, 1995, p.44).

function Utility-Based-Agent(percept)
static: a set of probabilistic beliefs about the state of the world
Update-Probs-for-Current-State(percept,old-action)
Update-Probs-for-Actions(state, actions)
Select-Action-with-Highest-Utility(probs)
return action

Table 3.5: Utility-based agent.

Utility-based agents try to maximize their own "happiness" which is expressed with a so called utility function (Niederberger & Gross, 2002, p.33).

3.4 Evaluation Criteria

Any intelligent system that involves integration of many components* is designed to engage in certain activities; taken together, these activities constitute its functional capabilities. In this section, we will discuss the capabilities that a cognitive architecture can support and what the architecture as a system should do towards fulfilling those capabilities.

3.4.1 The behavioural capabilities of an agent:

The behavioural capabilities of an agent cover its interaction with the world and the other characters (Laird, 1999). In this section we will concentrate on the characteristics of behavioural capabilities that seem to be generally useful for agents.

Brooks (1997, p. 402) considered some of the requirements for creatures (agents):

- A creature must cope appropriately and in a timely fashion with changes in its dynamic environment.
- A creature should be robust with respect to its environment. Minor changes in the properties of the world should not lead to total collapse of the creature's behaviour; rather one should expect only a gradual change in capabilities of the creature as the environment changes more and more.
- A creature should be able to maintain multiple goals and, depending on the circumstances it finds itself in, change which particular goals it is actively pursuing; thus it can both adapt to surroundings and capitalize on fortuitous circumstances.
- A creature should do something in the world; it should have some purpose in being.

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* For further details about agents' components see (Dörner,1999; Wooldridge & Jennings, 1994; Schmidt, 2002).

In addition, Laird and Van Lent (1999) argued that an effective artificial intelligence engine should support agents that are:

1- Reactive. **2-** Context Specific. **3-** Flexible. **4-** Realistic. **5-** Easy to develop.

Moreover, they emphasized that each of the components of the artificial intelligence engine must be carefully designed to implement the five requirements above.

Furthermore, Laird (1999) defined the following capabilities that should be also considered:

1. **Human sensing:** The ability of a character to sense things in the environment should be similar to the abilities of a human in the game. The character should not have superhuman abilities, such as seeing through walls (unless the character is superman) and should not have subhuman abilities (being unable to hear someone running up from behind in a quiet room).
2. **Human actions:** A character should be able to perform actions in the environment that correspond roughly to what a human could do in a similar environment.
3. **Human-level reaction times:** Humans do not respond instantaneously to changes in their environment, nor do they take arbitrarily long to respond (unless distracted).
4. **Spatial reasoning:** Many games are only 2D Cartesian grids where spatial reasoning is straightforward. However, the topology of a game from the standpoint of a character can be complex as obstacle, shortcuts, and a third dimension are added.
5. **Memory:** Most current game characters can be described as, "out of sight, out of mind", which leads to very inhuman-like behaviour. Thus, complex characters need to maintain memories of the world and have a model of how the world changes over time.
6. **Common sense reasoning:** This is the most dreaded of all classes of reasoning in AI because it is completely ill-defined. The only viable approach seems to be to determine what knowledge is necessary for the

tactics you wish to encode in your character and then encode the necessary common-sense knowledge to support those tactics. But this is insufficient if you wish to develop characters that develop their own tactics.

7. **Goals:** Characters must have a purpose, some goal they are trying to achieve. Often, there will be multiple goals, and the character has to decide which one to pursue or which actions pursue multiple goals. The goals should drive the actions of the character.
8. **Tactics:** A character should have a variety of tactics or methods that can be applied to achieving goals.
9. **Planning:** Planning provides the ability to try out actions internal, discover consequences, avoid death and destruction. Many of the benefits of planning can be compiled into a knowledge base when you know the world and goals beforehand.
10. **Communication and coordination:** For many games, the underlying goals for the characters require that they cooperate with other characters, and possibly the human player. The characters need to communicate in realistic ways and coordinate their behaviour as would humans.
11. **Learning:** For most games, learning can be avoided. It is only an issue for characters that have prolonged interactions with the human players. Learning is sometimes difficult to implement and can lead to unexpected and undesirable behaviour unless carefully controlled. However, Bradshaw (1997, p.7) noted that ideally, an agent that functions continuously in an environment over a long period of time would be able to learn from its experience.
12. **Unpredictable behaviour:** As with all of the capabilities covered here, non-determinism itself is less important than the illusion of unpredictability. It also depends on context. When there is only one right thing to do, then being predictable is fine. However, if a character has a sufficiently broad and rich set of fine-grained responses, its behaviour may be very difficult to predict.

13. **Personality:** Personality can be thought of what distinguishes one character from another above and beyond gross characteristics such as physical build and general mental capability.
14. **Emotions*:** Unfortunately, there are no comprehensive computational models of how emotions impact behaviour. What are the triggers for anger? How does anger impact other behaviours? However, as with personality, the expression and influence of emotion may be critical to creating the illusion of human behaviour.
15. **Physiological stressors:** In addition to emotions, there are other physiological changes that happen to people that in turn impacts their behaviour. In computer games, there is often a collective component of health, although the level of health rarely changes the behaviour of a character except when it goes down to zero (and the character dies). Other stressors include fatigue, heat, chemicals, radiation, ..etc.

3.4.2 Capabilities related to learning:

Introduction:

It is generally accepted by the artificial intelligence community that learning is a desirable and useful capability of a generally intelligent agent. This learning can take a number of forms, and the matter of which type of learning is most appropriate depends both on the researcher and the particular agent in question. Some systems include mechanisms for multiple learning methods in order to various components of their system to learn in their own ways. An agent is considered learnable when there are adaptive changes in its behaviour based on its previous experience (Franklin & Graesser, 1997). In the following, briefly

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* For further details about agents' emotions and facial expressions see (Kaiser et al. ,1998; Kaiser & Wehrle, 2001; Moldt & von Scheve, 2001; André et al., 2000; Bui et al. , 2001; Bartneck, 2001; Belavkin, 2004; Scheutz et al. , 2000; Scheutz, 2002; Wehrle, 1998; Rickel et al., 2001).

definitions of essential terms demonstrated by University of Michigan (artificial intelligence center*) will be discussed and for further details about agents in general and agents' criteria see (Alonso et al. , 2001; Wallace & Laird, 2003; Ekdahl, 2001; Horn et al. , 1999; Aylett & Luck, 2000; Floridi & Sanders, 2001; Norman & Long, 1995; Stahl, 2004).

1- Reflexive learning:

Generally, reflexive learning is learning that is done "automatically". Reflexive systems learn everything, even knowledge that does not promise to enhance the agent's behaviour. This extra knowledge threatens to slow the agent, since it must be searched each time the agent attempts to retrieve a piece of knowledge. An agent learns reflexively when there is no decision about when to learn. Reflexive mechanisms are generally architectural; thus, what is learned and the resource from which the information is learned is usually also determined without explicit deliberation. The advantage of a reflexive approach is speed in what is learned. The disadvantages come from investing too much time in learning, especially when the utility of what is being learned is poor.

A general paradigm for behaviour is "Perceive-Think-Act". However, in order to react quickly to dynamic environmental events, some architectures respond instantly to external stimuli, a quality often called reflexiveness. This may lend the system some extra speed when the event has been experienced previously (i.e., the reflex may be learned as well as innate) and the reaction can be performed instantly without having to plan a response. Other systems always deliberate before acting.

2- Monotonic vs. non-monotonic learning:

If an agent may not learn any knowledge that contradicts what it already knows then it is said to learn monotonically. For example, it may not replace a statement with its negation. Thus, the knowledge base may only grow with new facts in a monotonic fashion. The advantages of monotonic learning are greatly

* http://ai.eecs.umich.edu/cogarch0

simplified truth-maintenance, and greater choice in learning strategies. Since learning consists of the addition of new facts to the database, it may not be appropriate for all environments, although many simulated environments may be assumed to be consistent. In these cases a non-monotonic learning method is necessary.

An agent that may learn knowledge that contradicts what it already knows is said to learn non-monotonically. So, it may replace old knowledge with new if it believes there is sufficient reason to do so. The advantages of non-monotonic learning are increased applicability to real domains, and greater freedom in the order things are learned in. Architectures that are constrained to add only knowledge consistent with what has already been learned are said to learn monotonically.

3- Learning by analogy:

Learning by analogy generally involves abstracting details from a particular set of problems and resolving structural similarities between previously distinct problems. Analogical reasoning refers to this process of recognition and then applying the solution from the known problem to the new problem. Such technique is often identified as case-based reasoning. Analogical learning generally involves developing a set of mappings between features of two instances.

4- Learning by abstraction:

Contrasted with concept acquisition, abstraction is the ability to detect the relevant or critical information and action for a particular problem. Abstraction is often used in planning and problem solving in order to form a condition list for operators that lead from one complex state to another based on the criticality of the precondition. For instance, in an office environment, a robot with a master key can effectively ignore doors if it knows how to open doors in general. Thus, the problem of considering doors in a larger plan may be abstracted from the problem solving. This can be performed by the agent repeatedly to obtain the most general result.

5- Learning by instruction:

An agent that is given information about the environment, domain knowledge, or how to accomplish a particular task is said to be able to learn from instruction. Some instruction is given by a programmer, who simply gives the agent the knowledge in a sequential series of instructions. Other learning is interactive; the programmer is prepared to instruct the agent when the agent lacks knowledge and requests it. This last method supports experiential learning in which a teacher may act as both a guide (when called upon) and as an authority (when the agent is placing itself in danger or making a critical mistake).

6- Learning from experimentation:

Learning from experimentation, also called discovery, involves the use of domain knowledge, along with observations made about the environment, to extend and refine an agent's domain knowledge. An agent manipulates its environment to determine new information.

7- Generalization and transfer learning:

Generalization is the ability to apply knowledge and information gained in completing some task to other tasks and situations. Humans generalize routinely. Generalization can result from a number of different learning strategies including explanation-based learning, analogical learning, and abstraction learning. The generality of an architecture is an explanation of the types of tasks and environments the architecture can successfully deal with. This can be thought of as an effect of an architecture's versatility and taskability.

Transfer learning is capability that comes from generalization and is related to learning by analogy. Learned information can be applied to other problem instances and possibly even other instances. Three specific types of learning transfer are normally identified:

1. **Within -Trial:** Learning applies immediately to the current situation**.**
2. **Within-Task:** Learning is general enough that it may apply to different problem instances in the same domain.
3. **Across-Task:** Learning applies to different domains.

3.4.3 Capabilities related to planning:

1- Coherence:

Coherence refers to an agent's ability to resolve conflicts between competing or conflicting goals. Moreover, even though many behaviours may be active at once, or may be actively switched on or off, the creature should still appear to an observer to have coherence of actions and goals. It should not be rapidly switching between inconsistent behaviours, nor should two behaviours be active simultaneously, if they interfere with each other to the point that neither operates successfully (Brooks, 1991, p.46).

2- Deliberative and context specific:

Wooldridge and Jennings (1995, p.42) defined deliberative agent or agent architecture as:

"One that possesses an explicitly represented, symbolic model of the world, and in which decisions (for example about what actions to perform) are made via symbolic reasoning".

Context specific agents ensure that their actions are consistent with past sensor information and the agent's past actions (Laird & van Lent, 1999, p.579).

3- Veracity:

Veracity is the assumption that an agent will not knowingly (intentionally) communicate false information (see: Wooldridge& Jennings, 1995).

4- Taskability:

The taskability of an architecture is its ability to perform different tasks based on external commands from a human or from some other agent. For instance, can the architecture be asked to do various tasks without having to be reprogrammed or rewired? (Laird, 1991, p.12). The more tasks an architecture can perform in response to such commands, and the greater their diversity, the greater its taskability (Langley& Laird, 2002, p.19).

5- Reactivity and persistence:

Reactive agent means that the agent is one that perceives its environment, recognizes features of it, maintains an ongoing interaction with it, and responds to changes that occur in it (in a timely manner for the response to be useful) (Winikoff et al, 2001; Laird & Van Lent, 2000; Franklin & Graesser,1997; Bradshaw, 1997). We can measure an architecture's reactivity in terms of the speed with which it responds to unexpected situations or events, or in terms of the probability that it will respond on a given recognize-act cycle. The more rapidly an architecture responds, or the greater its chances of responding, the greater its reactivity (Langley& Laird, 2002, p.21).

Fully reactive agent has no memory, thus it does not have state, and it just responds to stimuli. Reactive agent is characterized by a direct connection between sensors and effectors. A fully reactive agent has several advantages because its behaviour is linked directly to sensing, and it is able to respond quickly to new changes in the environment and those reactions are specific to the current situation (Laird & van Lent, 1999, p.579). Wooldridge and Jennings (1995) defined a reactive architecture to be one that does not include any kind of central symbolic world model, and does not use complex symbolic reasoning.

Despite the importance of reactivity, we should note that, in many contexts, persistence is equally crucial. An architecture that always responds immediately to small environmental changes may lose sight of its longer-term objectives and oscillate from one activity to another, with no higher purpose. We can measure persistence as the degree to which an architecture continues to pursue its goals despite changes in the environment. Reactivity and persistence are not opposites, although they may appear so at first glance. An agent can react to short-term changes while still continuing to pursue its long-term objectives (Langley& Laird, 2002, p.21).

6- Scalability:

An architecture is considered to be scalable if it can handle increasingly complex problems that demand a greater amount of knowledge. The scalability depends on whether the architecture can scale up to bigger and bigger problems with more knowledge? (Laird, 1991, p.12). Because architectures must handle tasks and situations of different difficulty, we want to know its scalability. Making architectures more scalable with respect to increased knowledge remains an open research issue (Langley& Laird, 2002, p. 20).

7- Efficiency:

The efficiency of an architecture is its ability to do a task within certain time and space constraints. And because cognitive architectures must be used in practice, they must be able to perform tasks within certain time and space constraints. Thus, efficiency is another important metric to utilize when evaluating an architecture. We can measure an architecture's space and time efficiency as a function of task complexity, environmental uncertainty, length of operation, and other complicating factors. We can examine an architecture's complexity profile across a range of problems and amounts of knowledge. The less an architecture's efficiency is affected by these factors, the greater its scalability (ibid).

In summary, an agent can be measured for efficiency in three ways*:

1. The implicit representation of state in the form of the task queue is minimal.
2. The automatic failure recovery occurs very fast.
3. Operations that are no longer of use can be aborted.

3.4.4 Capabilities related to robotic agent:

1- Autonomous:

Autonomy concept refers to goal-directedness, proactive and self-starting behaviour (Bradshaw, 1997, p.8). Autonomic agents operate without the direct intervention of humans or others, and have some kind of control over their actions and internal state (Wooldridge& Jennings, 1995). One can consider that autonomy is the first order, while self-reflection is the second order of autonomy concept.

* For further details see (http://ai.eecs.umich.edu/cogarch0/atlantis/issue/eff.html).

Without this property –autonomy-, an agent would no longer be a dynamic entity, but rather a passive object. Subsequently, autonomous agents have individual internal states and goals, and they act in such a manner as to meet its goals. In addition, by autonomy, we mean the ability of the systems to make their own decisions and to execute tasks on the designer's behalf (Alonso, 2002, p.25).

In addition, agents are useful when we state something that we want to achieve, then we give a very abstract specification of the system, and let the control mechanism figure out what to do, knowing that it will act in accordance with a model. In other words, we give the system general information about the relationships between objects, and let its figure out what to do. Therefore, an agent should know about the world (its environment) in order to be able to accomplish its goals, and when the goals or the environment change, the agent must change its model as well or modify it in order to cope with the changing of its goals or its environment. This type of agent is called autonomous agent, which is characterized by the following:

- An autonomous agent should be capable of flexible autonomous action in order to meet its design objectives.
- An autonomous agent can act randomly until it has gathered enough information from its environment to act rationally.
- An agent is called autonomous if it operates completely autonomously, and when it decides itself how to relate its sensor data to motor commands in such a way that its goals are attended to successfully.
- Autonomous agents have the ability to take over some human tasks and interact with people in human like ways.
- An agent is autonomous to the extent that its action choices depend on its experience, rather than on knowledge built in by the designer (Russell & Norving, 1995). Moreover, in unknown scenarios where it is difficult to control directly the behaviour of our systems, the ability of acting autonomously is essential (Alonso, 2002, p.25).

2- Versatility:

The versatility of an architecture is a measure of the types of goals, methods, and behaviours the architecture supports for the specified environments and tasks (Laird, 1991, p.12). The agent may perform sequences of tasks to achieve a goal. It may perform different instances of several different tasks aimed at different goals concurrently. However, these tasks must be integrated to share knowledge and results. For example, models of the environment should inform diagnosis, which should in turn provide a basis for reaction or planning. Conversely, reactions and plans should influence prospective models of the environment and, in some cases, might also be directed towards evidence gathering for diagnosis (Hayes-Roth, 1991, p.79).

3- Rationality and realistic:

Rationality is the assumption that an agent will act in order to achieve its goals, and will not act in such a way as to prevent its goals being achieved - at least insofar as its beliefs permit (Wooldridge& Jennings, 1995). Bratman (1988) described rational behaviour as the production of actions that further the goals of an agent, based upon her conception of the world. The rationality of an architecture is a measure of consistency. That means are the actions it performs always consistent with its knowledge and goals? (Laird, 1991, p.12). We can measure an architecture's rationality by examining the relationship between its goals, its knowledge, and its actions (Langley& Laird, 2002, p. 19). For instance, Newell indicated that if an agent has knowledge that one of its actions will lead to one of its goals, then the agent will select that action. Since an architecture makes many decisions about action over time, we can estimate this sense of rationality by noting the percentage of times that its behaviour satisfies this criterion (ibid). Realistic agents behave like humans. More specifically, they have the same strengths has human players as well as the same weaknesses (Laird & van Lent, 1999, p.579). Also the agent should act to achieve its goals and in the time should care about the surrounding environment.

4- Personality, sociability and communication:

Personality: Personality is the capability of manifesting the attributes of a "believable" character such as emotion (Bradshaw, 1997, p.8).

Socialability: Socialability means that the agent has the ability to interact in a friendly way with other agents (and possibly humans) via some kind of agent-communication language, and perhaps cooperate with others (see: Wooldridge& Jennings, 1995; Franklin & Graesser, 1997).

Moreover, friendliness or pleasant social relations mark the interaction. An agent must also show a social attitude. In an environment populated by heterogeneous entities, agents must have the ability to recognise their opponents, and form groups when it is profitable to do so (Alonso, 2002, p.26).

Communication: Communication ability is the ability to communicate with persons and other agents with language more resembling humanlike "speech acts" than typical symbol-level program-to-program protocols (Bradshaw, 1997, p.8). Communicative agent is able to engage in complex communication with other agents, including people, in order to obtain information or to achieve some goal. Moreover, agents begin to act as a society when agents can be engaged in multiple, parallel interactions with other agents. The interaction becomes most complex when systems involving many heterogeneous agents that can coordinate through cooperative and/or competitive mechanisms (such as negotiation and planning).

5- Execution:

Real-time execution and interruptible execution are necessary because most tasks of interest require that an agent responds enough to react to changes in the environment and response to changes requires that an agent be able to stop one activity and switch to another (Lee & Yoo, 1999, p. 133).

Real-time execution: The agent needs to be responsive to its environment and predictably fast enough to act on the changes in the environment (ibid). **Interruptible execution:** A dynamically changing environment demands that the agent be able to stop its current activity and gracefully switch to other more urgent or higher priority activities (ibid).

Temporal continuous execution: A temporally continuous agent is the agent that runs continuously or continues execution rather than a single input and a single output agent, and then terminate. Temporal continuity is persistence of identity and state over long periods of time (Bradshaw, 1997, p.8).

6- Benevolence:

One of the most important issues to consider when designing an agent is whether the different agents will be benevolent or/and competitive.Benevolence is the assumption that agents do not have conflicting goals, and that every agent will therefore always try to do what is asked of it (see: Wooldridge& Jennings, 1995). Moreover, believable agent has a well-defined believable personality and emotional state.

7- Believable:

Believable agents provide the illusion of life, thus permitting the audience's suspension of disbelief (see: Wooldridge& Jennings, 1995). A key component of such agents is emotion. Agents should not be represented in a computer game or animated film as the flat, featureless characters that appear in current computer games. They need to show emotions; to act and react in a way that resonates in tune with our empathy and understanding of human behaviour (ibid).

8- Cooperative:

Cooperation here means that the ability to perform some activity in a shared environment with other agents. Activities are often coordinated via plans or some other process management mechanism. An agent that is able to coordinate with other agents and possibly humans via some communications language to achieve a common purpose or may in some circumstances work together to achieve some goal is considered cooperative (see: Bradshaw, 1997, p.8). In order to co-operate, agents need to possess a social ability (i.e., the ability to learn and/or interact with their external environment).

9- Mobility:

Mobility is the ability of an agent to move around an electronic network (see: Wooldridge& Jennings, 1995; Bradshaw, 1997, p.9) and/or is the ability of an agent to transport itself from one machine to another (Franklin & Graesser, 1997). Mobility is being able to migrate in a self-directed way from one host platform to another (Bradshaw, 1997, p.8).

3.4.5 Capabilities related to interaction with environment

1- Flexible:

Flexible agent has the ability to dynamically choose which actions to invoke in response to the state of its external environment. Moreover, flexible agents have a choice of high level tactics with which to achieve current goals and a choice of lower level behaviours with which to implement current tactics (Laird & van Lent, 1999, p.579).

2- Proactive:

Proactive agents do not simply act in response to their environment; they are able to exhibit goal-directed behaviour by taking the initiative (see: Wooldridge& Jennings, 1995). Proactive agent implies the use of goals and modifies the agent's internal execution cycle.

An important aspect of proactiveness is the persistence of goals. If a plan for achieving a goal fails then the agent will consider alternative plans for achieving the goal in question (Winikoff et al, 2001). Proactiveness means that the agent could do things; generate and attempt to achieve goals (able to exhibit goal-directed behaviour); take the initiative; recognize opportunities; engage in planning; and goal directed behaviour. Proactive agent will actually estimate the environment for events and other messages to determine what action it should take to achieve its goals. In short, an agent can decide what it can do.

3- Adaptivity:

Adaptivity is being able to learn and improve with experience (Bradshaw, 1997, p.8). An agent is considered adaptive when the agent automatically customizes itself to the preferences and to modify its behaviour based on its experience. In other words, it should be able to learn, adapt to changes in its environment, and would in some occasions attempt to adapt itself to deal with new or changing goals.

In general, systems with adaptive functionality are doing the following (Erickson, 1997, p.82):

- **Noticing:** Trying to detect potentially relevant events.
- **Responding:** Acting on the interpreted events by using a set of action rules, either by taking some action that affects the user, or by altering their own rules (i.e., learning).
- **Interpreting:** Trying to recognize the events (generally, this means mapping the external event into an element in the system's 'vocabulary') by applying a set of recognition rules.

Moreover, the agent should be capable of responding to other agents and/or its environment to some degree, and it should be able to react to a simple stimulus to make a direct, predetermined response to a particular event or environmental signal.

Such adaptive functionality holds great promise for making computer systems more responsive, personal, and proactive. However, while such functionality is necessary for enhancing systems, it is not sufficient. Adaptive functionality does no good if it is not, or can not be used; it may do harm if it confuses its users, interferes with their work practices, or has unanticipated effects (ibid). There are many chances for adaptive functionality to fail. The system may fail to notice a relevant event (or may mistakenly notice an irrelevant event). It may misinterpret an event that has been noticed. Or it may respond incorrectly to an event that it has correctly noticed and interpreted (that is, the system does everything right, but the rules that it has for responding to the event don't match what the user expects). These failures are important to consider because they have a big impact on the user's experience (ibid).

3.4.6 Capabilities related to agent's performance

1- Intelligent:

Brooks (1997, p.395) noted that:

"I and others believe that human-level intelligence is too complex and too little understood to be correctly decomposed into the right subpieces at the moment, and that even if we knew the subpieces we still wouldn't know the right interfaces between them. Furthermore we will never understand how to decompose human-level intelligence until we've had a lot of practice with simpler intelligences."

Whatever the term intelligent agent means, an agent have to show some of the following features to consider an intelligent agent: It should have a basic set of attributes and facilities. Moreover, it must be formalized by knowledge (i.e., beliefs, goals, desires, intentions, plans, assumptions) and be able to act on this knowledge. It should be able to examine its beliefs and desires, form its intentions, plan what actions it will perform based on certain assumptions, and eventually act on its plans. It should be able to choose an action based on internal goals and the knowledge that a particular action will bring it closer to its goals. It must be able to interact with other agents or human using symbolic language. It should have a model of rational human thinking strategy.

2- Saliency:

Saliency refers to an intelligent agent's ability to act appropriately to the current situation. In other words, The behaviours that are active should be salient to the situation the creature finds itself in, for example, it should recharge itself when the batteries are low, not when they are full (Brooks, 1991, p.46).

3- Adequacy:

This attribute is generally associated with robotic agents. Brooks (1991, p.46) noted that adequacy means that the behaviour selection mechanism must ensure that the long term goals that the creature designer has for the creature are met (i.e., a floor cleaning robot should successfully clean the floor in normal circumstances, besides doing all the ancillary tasks that are necessary for it to be successful at that).

4- Perception and prediction:

Prediction refers to an architecture's ability to predict what the state of the world is or might be, what things might happen in the outside world, and what other things might happen as a consequence of the agent's actions. In a computer game, the character can decide what the next action should be based on what its observations and its historical data. From this perspective, the character is similar to a baby trying to create a model of the world based on the information it has access to (Pisan, 2000, P. 67).

5- Providing explanations for decisions:

It is often desirable that an agent provides explanations of its actions. Providing explanations for decisions is the ability to query the agent about things like past episodes, or the current state of the world. If not posed in natural language, some of these queries are quite simple if the agent simply has episodic or state information immediately available. Moreover, in multi-agents environment, the agent can summarize local situations and report them to other agents. The reports should provide the receiving agents with a global view of the situation and allow them to coordinate with other agents effectively (Lee & Yoo, 1999, p. 134).

Discussion

In this chapter, we have demonstrated the area of agents within the artificial intelligence and computer science communities. We have reviewed the framework of the agent research and that included a general description of an intelligent agent, definitions, basic fundamentals of agents, types of agents and evaluation criteria of agents. However, in spite of the big efforts spent on research in the agent's area there is no agreement about what should be meant by agent. In fact, since the concept of "agent" is so unsatisfactorily defined, it appears as everything could be called agent. Yet, an intelligent agent from our point of view is the agent that shows at least autonomous capability (act independently) and it should have capabilities and properties such as: learning, planning, robotic tasks, interaction with environment and agent's performance. In other words, since capability is something that an architecture is able to do, therefore understanding agent capabilities and properties can help us to identify the techniques and methods that were used to construct a particular architecture or architectural components. These properties have often been studied as part of artificial intelligence research because there is agreement between researchers that the behaviour of a system, with regards to intelligent architectures, refers to the physical agent's capability of navigating through its environment, and how it uses knowledge it possesses to reach its goals. Furthermore, fundamentals of an agent have been presented. Moreover, we have reviewed several of the many aspects that have classified agents. Finally, we have focussed mainly on evaluation criteria of agents, which have been considered as clear set of standards available to analyze systems. Such criteria will be used in next chapter to evaluate our autonomous agent (PSI).

Chapter

4

PSI-Theory

Fundamentals & Related Work

Summary

This chapter provides an overview of the framework of PSI-theory and we will describe the internal structure of the motivated emotional-cognitive system. In section 4.1, we will provide a general description of basic units of PSI–agent and the process of running intentions. In section 4.2, description of PSI-motivators, affiliation motive (the need for affiliation), uncertainty motive (the need for certainty) and incompetence motive (the need for efficiency signals) will be discussed. PSI- emotions, selection threshold and resolution level will be explained in section 4.3. As well, action regulation will be discussed in this section too. In Section 4.4, we will review and discuss related work to our research. Such as, a comparison between PSI-model and human behaviour in a complex and dynamic task, a comparison between PSI-emotions and human emotions in a complex task, and the simulation of social emotions, especially for aggression in groups of social agents.

4.1 Fundamentals

4.1.1 Introduction:

PSI is part of a theoretical approach which Dietrich Dörner calls "synthetic psychology", in which Dörner described motivation and emotion in terms of information processing. This approach includes assumptions about the dynamics of emotions and motivations and tries to analyze psychological processes by simulating them as processes of information processing. Furthermore, the approach explicitly goes beyond the mere cognitive capacities and directly integrates perception, body movements, actions, emotions and motivations.

In consideration to the relationship between psychology and artificial intelligence, Dörner believes that:

1- Artificial intelligence could learn a lot from psychological research (i.e., building intelligent systems that model psychological phenomena should have the ability to empirically predict human behaviour and to solve problems by the way humans do (human-like strategies).

2- Intelligent system that imitates human behaviour should not only imitate just correct behaviour, but also it should imitate human errors.

In addition, Dörner & Hille (1995, p.3832) argued some hints about what is necessary to construct autonomous robots. They had suggested that such a robot should be supplied with:

- A motive of curiosity to acquire knowledge about its environment in case it is possible and desired.
- A mechanism of action or motive selection to decide autonomously what to do by taking into consideration the situation.
- Internal parameters which determinate the "personality" and may create different behaviour types of robots for different tasks or times.
- Emotions in terms of a possibility to provide plastic behavior, which fits to the current situation.

4.1.2 PSI-agent:

PSI-theory is partially implemented as a computer program[*] which describes the informational structure of an intelligent, motivated, emotional agent (PSI) that is able to survive in arbitrary domains of reality. PSI's robot can be imagine as a steam engine that has a sensory and a motor system and is motivated too. For example, PSI has hunger, thirst, and a need for competence and certainty. Figure 4.1 shows PSI- agent and figure 4.3 shows a rough sketch of PSI's internal structure.

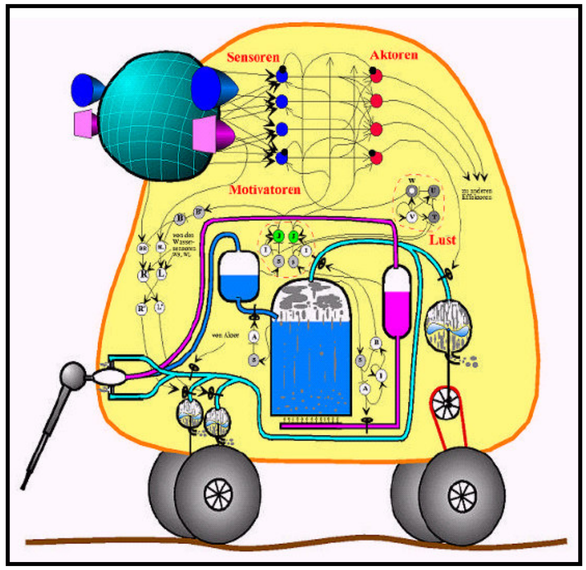

Figure 4.1: PSI-agent.

The robot is able to perceive objects and situations, to plan, to remember sequences of actions which proved to be successful in the past, to learn goals and switch between different tasks etc..(see Dörner et al., 2002; Dörner, 2003). The sensory system comprises two kinds of "noses", one for smelling water and another one for smelling fuel.

Additionally the system is equipped with one eye to be able to identify optical patterns. PSI-agent is able to move and to suck liquids by a suction pump. In PSI cognition, motivation and emotion are conceptualized as information processes, generally as "calculation" (Dörner & Starker, 2004). PSI architecture has ability not only to achieve some desired goal or result without requiring change in the algorithm, but also to yield a solution regardless of changing in the problem domain. In addition, any change to domain could readily be incorporated in the solution.

* PSI-theory was programmed by Dietrich Dörner and Jürgen Gerdes and the theory was programmed by using Pascal language.

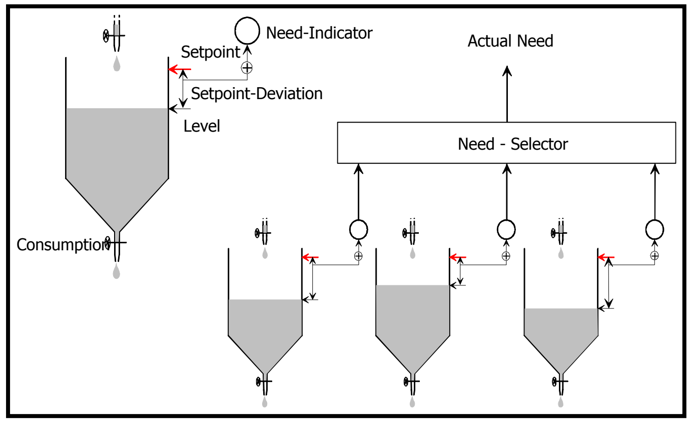

Figure 4.2: A system for motivation. Source: (Dörner & Gerdes, 2005, P. 39).

Dörner and Gerdes (2005, p. 39) noted that: "The energy store of an organism can be considered as a tank*, as exhibited in figure 4.2. This tank empties in the course of the time by consumption (dependent on basal metabolism + activity of the organism).This tank has a setpoint; it should be filled!

If there is a setpoint-deviation there is a need. This need is the basis of the motivation. There exists a need indicator which is dependent on the extent of the deviation. A lot of such "tanks" can be found in an organism. First there are tanks for the "existential" needs; hunger, thirst and pain may be the most important. A pain indicator signals that the structure of the organism is hurt (the "tank" of structural intactness deviates from its setpoint). Very important are tanks for attachment, for certainty and for competence. The attachment tank is filled up by "signals of legitimacy" (as Boulding 1974, p. 196 called them). Such signals indicate that an organism is accepted as a member of a group and can expect help and assistance. A smile or body contacts (tenderness) may be the most important "signals of legitimacy" for humans. – The need for certainty is the need to be able to predict the course of events and the effects of one's own actions. The "certainty tank" is filled by predictions which turn out to be true, whereas it is emptied by events which are unexpected. – The competence tank is filled by successful actions and emptied by failures. Especially the competence and certainty tanks are important for emotions." lately

* "Tank" should not be understood literally; the tank in this case could be a neuronal circuit, the activity of which could be enhanced or inhibited (Dörner, 1997, p. 19).

4.1.3 Description of basic units of PSI:

The main objective of this section is to demonstrate some of the basic units and concepts of the computer simulated model of action regulation in complex domain (PSI) as they were described by (Bartl & Dörner, 1998; Gerdes & Strohschneider, 1991; Detje & Künzel, 2003).

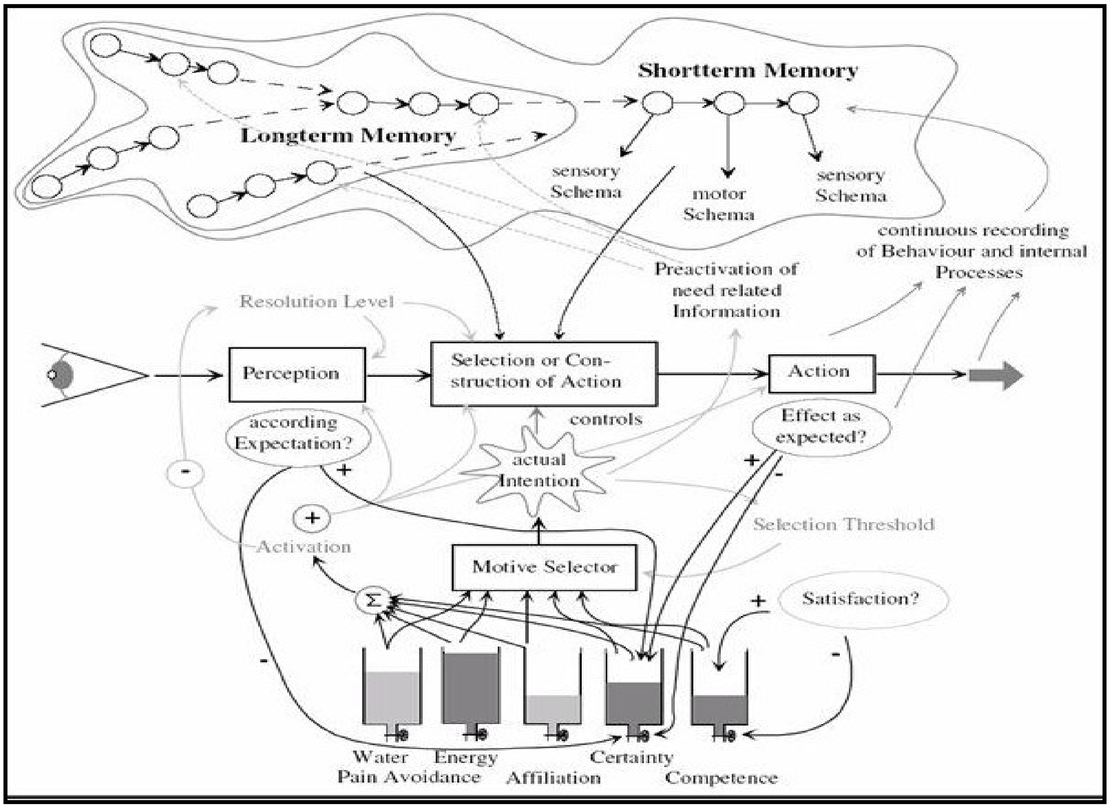

Figure 4.3: The internal structure of PSI.
Source: (Bartl & Dörner, 1998, p. 3).

At the bottom, the motivational system of PSI is symbolised by a number of water-tanks. These tanks are mechanical models of "motivators" (ibid, p. 3).

Intention:

An intention is a data structure consisting of information about the goal, about the present state and normally of more or less complete plans for achieving the goal (Bartl & Dörner, 1998). Because intentions control the action of PSI- robot, intention concept is considering the core of PSI-theory. Intention can be defined as a combination of the selected motive and the information connected with the active motivator within the memory network. Intentions are conceptualized as links between different parts of a memory structure. In other words, intentions include more than merely the goal to satisfy the needs. They also include a number of elements that contain context information, particularly history (of an intention), start-situation, available operators (plan), goal-situation, instrumentality, estimated time for success and remaining time (which lead to a certain degree of urgency), importance and estimated success probability "subject's competence" (Detje & Künzel, 2003, p.317). Furthermore, after an intention has been formed, PSI will "run the intention" to achieve the respective goal. Running an intention means running different processes through PSI's units as they will be illustrated as follow:

GENINT:

It stands for GENerate INTentions and is the information processing unit, which is responsible for constructing intentions (Gerdes & Stroschneider, 1991, p.3). Dörner and Hille (1995, p.3829) explained that: "Not every need creates all the time an intention. Sometimes we are not hungry, so there is no intention to eat. It generates intentions from the needs basically depending on the strength of the need. All the generated intentions are stored in the memory of intention till the underlying needs are satisfied. Most of the time there is more than one intention in this memory. It has to be decided which one to follow. This is the task of SELECTINT". GENINT retrieves the knowledge elements necessary for the completion of the structure of an intention: the respective need, the desired goal state(s), the plan or action sequence to reach it, and its importance and urgency. GENINT files these pieces of information in the intention memory MEMINT (Gerdes & Stroschneider, 1991, p.3).

SELECTINT:

Gerdes and Stroschneider (1991, p.3) noted that: "SELECTINT has the task of selecting the "ACTive INTention" (ACTINT), which is to govern action for the next period of time. The principle, according to which SELECTINT makes this selection, is basically an "expectation-value-principle", using the importances and the estimated probabilities of success of the single intentions in MEMINT". Dörner and Hille (ibid, p.3829) indicated that selecting an intention is depending on the importance of the need, the urgency of the realization, and the competence of the artificial soul.

RUNINT:

It stands for RUN INTentions and is thus the system for handling the execution of intentions. In principle, RUNINT takes up the active intention and tries to execute the operations, necessary to reach the desired goal state. As a result of the activity of RUNINT, intentions are either satisfied or returned as uncompleted, for the time being (Gerdes & Stroschneider, 1991, p.3).

Dörner and Hille (1995, p.3829) noted that: "The realization of the leading intention can be done in three ways: Firstly, if the artificial soul has not got enough information about how to realize the intention, it explores how to do it. It gains knowledge about the satisfaction of the need. It learns. Secondly, the artificial soul may plan, if it has got enough knowledge but no plan. Finally, if it has got both, enough knowledge and a decent plan, the artificial soul acts, it uses well-known automatism."

PERCEPT:

Dörner and Hille (ibid, pp.3829-3830) noted that: "PERCEPT stands for perception. This procedure draws an image of the situation by looking at the reality. PERCEPT itself is influenced by the modulating parameters. For instance, the higher the rate of updating, the better the image of the situation. PERCEPT perceives the environment with the events that rise or satisfy needs and help or hinder the realization of an intention. PERCEPT noticed also the uncertainty of the situation. A high level of uncertainty means that a lot of events occurred unexpected ".

Moreover, As a result of the interaction of PERCEPT and RUNINT the system also generates a "record memory" by storing images of the past. Another result of this interaction is the creation of an "expectation horizon", the system's knowledge about the future. It is constructed using the record memory, the current activity of RUNINT and the general knowledge base (Gerdes & Stroschneider, 1991, p.3).

4.1.4 The process of running intentions:

Gerdes and Stroschneider (1991, pp.6-10) have been discussed the functions of RUNINT that has to fulfill in successfully completing a selected intention as follow: Firstly, RUNINT has to know about one (or more) goal-state(s) of the given intention: It has to know, in which direction it has to move to satisfy the underlying need. RUNINT also has to know where it is. It must have knowledge about the given situation, about environmental changes in time and about environmental changes that result from its own operations. Then, if there is knowledge about the operations necessary to reach a goal, RUNINT has to have access to this knowledge and has to be able to execute the operations. If there is no such knowledge, RUNINT should be able to find new ways to fulfill the intention.

RUNINT must have the ability to generate solutions to problems by way of planning. This can be done via "interpolative planning", the internal construction of new sequences or combinations of already known operators. It can also be done via "synthetic planning", the construction of new operators and operator sequences. To that end, RUNINT must have the ability to actively explore its environment (ibid, p.6). The knowledge about goal-states, about the given situation and about existing plans, comes with the active intention ACTINT. Knowledge about environmental changes comes from the HYPERCEPT-process (PERCEPT). RUNINT, in turn, is able to direct HYPERCEPT. That is how RUNINT searches actively for certain information and can, e.g., change the resolution level of HYPERCEPT for closer inspection of interesting objects. RUNINT, of course, also has direct access to the triple-hierarchy and the record-memory for planning and the execution of operations (ibid, p.6).

As soon as PSI has discovered, that there are need-satisfying situations, it can form intentions. PSI can execute intentions on three different levels (ibid, pp.9-10):

1- **A level of automatic functioning**: At first, PSI tries to find sequences of Action-schemata in its knowledge base that might mediate between the given situation and the goal state. If such a macro-operator is found, it is executed straightforward ("automatic functioning").

2- **A level of internal planning**: Planning" is the next level of intention execution that is activated, if no macro-operator is found. planning works–in principle–something like this: If PSI knows any operators, that can be executed in the given situation, it will try to combine such operators by means of a hill-climbing heuristic (execute the one operator that yields the greatest step towards the goal) or a backward-search heuristic (search for operator-chains that have the goal-state as their expected outcome and an input element, that is closer to the given situation).

3- **A level of active exploration:** Only if planning falls, PSI switches to exploration as the third level of intention execution. Exploration leads to overt acts, influencing the environment. The first and most elaborate strategy of Exploration is hill-climbing. PSI searches for operators that are already known to be possible in the given situation. It then (internally) checks the outcome expectations of' these operators for their goal-distance and executes (in reality) the one operator that yields the greatest step towards the goal. If the goal isn't yet reached, this procedure is repeated. PSI keeps a record of its activities, so that endless loops in this hill-climbing process can be avoided.

Hill-climbing is, of course, only possible if there is a hill to be climbed, that is, if PSI knows a goal state for the predominant need. If there is only a need, but no knowledge of a satisfying situation, or if there is such knowledge, but hill-climbing has failed, exploration process uses a strategy we call "try something new". With "try something new", PSI scans its operator list for operators, that might change the given situation and then PSI executes them.

4.2 PSI- Motivators

4.2.1 Introduction:

To be able to act autonomously is not only a matter of cognitive capabilities as the ability to learn and the ability to plan and to solve problems, but also is a matter of motivation too (Dörner, 1997). The main question that has been demonstrated by Dörner’s approach is: “which kinds of motives or needs are necessary and advantageous for an autonomous system to survive in a complex and changing environment (ibid, p. 17)”. Dörner showed that human beings have got many needs such as hunger thirst, but also affiliation and curiosity (Dörner & Hille, 1995, p.3829). So, existential needs are necessary and certain informational needs are advantageous. An autonomous system must have needs for energy and matter (for instance water). Additionally needs for affiliation, certainty and competence are advantageous. Therefore, when we want to simulate the life of an artificial system, these motives should be equipped (ibid). Thus, motivation is based on needs that indicate set-point –deviations of certain important variables of a system (e.g. disposable energy in terms of the charge of a battery in a battery–powered robot or in terms of glucose in the blood of man) (see: Dörner & Hille, 1995, p.3828; Bartl & Dörner, 1998, p.3; Hoyer, 2003, p.263).

4.2.2 Description of PSI-motivators:

PSI's behaviour is driven by various needs as shown in figure 4.4. Some arise periodically (e.g. hunger or so to speak "energy"), some originate from the environment (avoidance of danger), and some develop from internal settings (curiosity as a lack of knowledge). These needs are connected with certain goals. The connection contains the general way of satisfaction the need. For instance: hunger is connected with eating, thirst with drinking (Dörner & Hille, 1995, p.3829). PSI’s motivators are sensible for the level of a variable. Such variables could be water or energy resources of a system, temperature of a body or any other variable important for life or welfare of a system. When a variable deviates from its set point, a motivator becomes active. In this case, a need exists and the motivator will try to launch activities to restore the set point value of the respective variable.

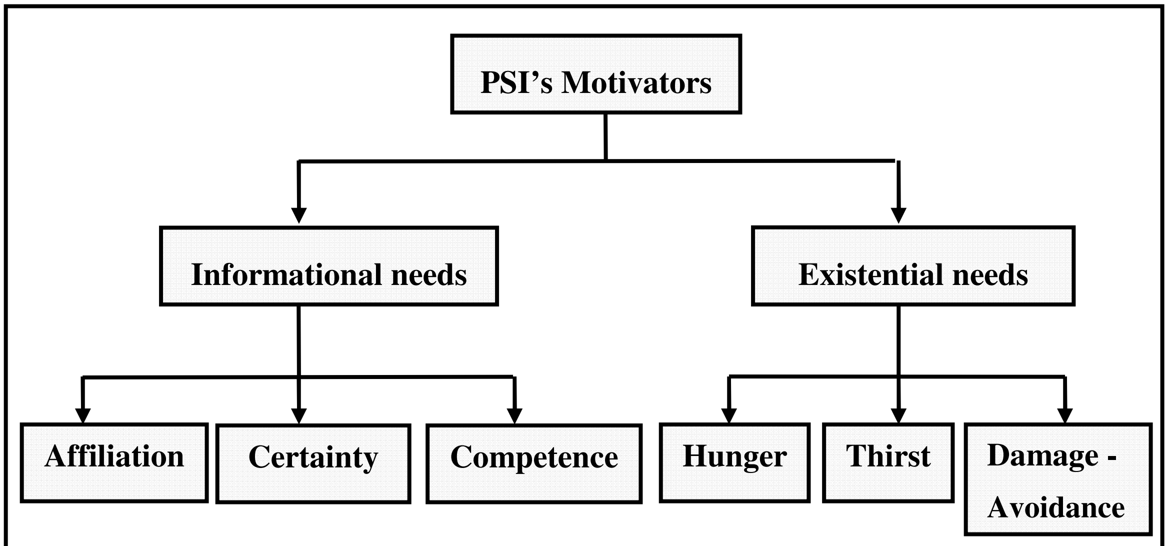

Figure 4.4: PSI's motivators.

Existential needs:

Dörner (1997, p. 19) called the needs for water and fuel (for energy) and the need to avoid pain (dangerous situations "e.g. falling rocks") existential needs. Naturally, needs for fuel and water are necessary. Without these needs PSI could not survive or could only survive in very benign environments (i.e., in environments which produce no or only few dangerous events).

Informational needs:

Beside existential needs, it is advantageous to have three kinds of informational needs. The informational needs are certainty (an expectation fulfilled) and uncertainty (an expectation unfulfilled), competence (fulfilment of needs) and affiliation (need for social contacts). These needs do not concern matter or energy, rather information.

According to (Gerdes & Strohschneider, 1991; Dörner,1997; Bartl, & Dörner,1998; Dörner, 1999; Dörner et al., 2002; Detje & Künzel, 2003; Elkady & Starker, 2005), PSI-theory is a conceptualization of several information processing units that interact with the systems knowledge base, a network of sensory schemata and motor programs that are related to a set of needs. PSI then is the interaction of these processing units and memory systems. The distinction between different memory systems is made on functional grounds. In general, all the knowledge of PSI is stored in one network. The knowledge-base is made up of three networks. Of course, these three networks are not independent of one other; rather they are linked by means of a tight net of relations of various types. The three networks of PSI are:

1- The sensory network stores schemata and images of phenomena, objects and situations, that is, the "declarative knowledge" of PSI.

2- The motor network contains the action programs of the system, ordered in a hierarchy of increasingly finer differentiations.

3- The motivational "network" is made up of a set of nodes that become active, when a corresponding state of deprivation exists. The size of the set-point-deviation determines the activation of this node and thus the importance of the intention to be formed.

The structure of a motivator within PSI with respect to the need for water, for example, is described by Dörner (1997, pp. 18-19; 2003, p. 75) as the following:

1. Firstly, there must exist a sensor for set-point deviations, which measures the water-level in the steam boiler.
2. Secondly, there can (but must not) exist internal regulators, which in the case of a set-point deviation try to re-establish homeostasis by refilling the steam boiler from the reserve tank.
3. This will bring a reduction of the set point deviation if there is enough water in the reserve tank. If internal regulation is not successful, a need-indicator will become active.

4. A need can activate external activities (i.e., activities changes in the environment directed towards a goal). A goal is a situation where a need can be satisfied.
5. Motivators are connected with a pleasure and a pain indicator. The pleasure indicator produces an internal signal, when a need is satisfied. This signal causes learning. The momentarily given situation is learned as a goal and the sequence of antecedent actions are learned as a behaviour program, which could produce the respective goal state.
6. The pain indicator becomes active, when a set-point deviation increases. The pain indicator produces leaning signals too. It causes avoidance learning. The respective situations should be avoided in the future.
7. Other motivators have the same structure, but have sensors not for the water level in a steam boiler, but for the level of other variables.
8. PSI' motivators are controlling different forms of behaviour as safeguarding-behaviour, aggression, flight, exploration.

4.2.3 Affiliation motive (the need for affiliation):

Basically, Affiliation motive is the need for social contacts and group integration. This need brings social groups into existence. By this need, the PSIs are stimulated to form groups and to help each other. Such a need is very helpful especially when a PSI arrives in a new and uncertain environment which it does not know. In such a case, an affiliation need motivates other PSIs to help the novice in the new environment and to show him where it could find water or fuel or to show him which roads are dangerous and; therefore, should be avoided (Dörner, 1997, p.19). Such an affiliation motive can be realised in a very simple fashion. The PSI should strive for "signals of legitimacy". With man, such signals of legitimacy comprise a smile, a clap on the shoulder and other forms of approval. Signals of disapproval serve as indicators for "non-affiliation" and will empty the "affiliation tank".

If we equip our PSIs with a tank, which is filled up by signals of legitimacy and which empties in the course of time and; therefore, must be refilled by looking for signals of legitimacy and if we add to this "tank of legitimacy" a sensor for the respective "legitimacy - level", we have established the basis of an affiliation need (ibid, p. 19). If we additionally program the PSIs in such a way that they produce signals of legitimacy only when they receive help, when a need is satisfied, another PSI, looking for legitimacy signals, will get such signals only if it provides need-satisfaction to another PSI. Hence, as signals of legitimacy are only given for helpful behaviour, for satisfying the needs of other PSIs, the PSIs must give help to receive signals of legitimacy (ibid, p. 19).

4.2.4 Uncertainty motive (the need for certainty):

What is a "certainty signal"? Dörner (2003, p. 76) explained that: "An organism steadily makes predictions of the future, be it in the form of calculations of the outcomes of its own actions or in the form of extrapolations of the course of events. These predictions normally are not conscious, but happen automatically and are present even with rather primitive animals. The course of events is not only predicted, but it is continually checked whether the predictions are correct. We normally do not notice these checks if their result is positive, but an organism will react with surprise or fright if such a check turns out to be negative."

Therefore, uncertainty motive is generally a need of information that is satisfied by "certainty signals". Dörner (ibid, p.75) described certainty as: "Certainty is the estimated degree of the ability to predict the course of events. Entropy or uncertainty is the degree of predictability of the environment, especially the degree of predictability of the consequences of ones own actions".

An important certainty signal is, for example, a correct prediction. By acting in a certain domain of reality, PSI will learn regularities of its environment. Therefore, it will be able to predict the outcomes of its actions and progress of events. If these predictions are correct, this is a certainty signal and will fill up the "certainty tank". In addition, PSI compiles knowledge by experience. It learns about the effects of operators in a specific domain of reality, learns goals and learns chains of events. Therefore, it is able to predict what will happen in the future (Bartl & Dörner, 1998). Certainty signals enhance the activity of the "certainty-neuron", whereas uncertainty signals diminish this activity (ibid).

If PSI meets a novel situation or if it turns out, that a certain action has not the foreseen consequence, PSI experiences uncertainly (Dörner, 1997, p. 20). Therefore, wrong predictions or unpredicted development of the chain of events mean uncertainty and will decrease the level of the "certainty tank". A decline in certainty leads to an increase of background control. Thus, If the "certainty tank" is to empty, PSI should activate actions that produce certainty signals. Actions, which produce certainty, are all kinds of activities that increase the knowledge about the environment. Such activities are for instance all kinds of explorative activities. For instance, observing the environment to find out the rules of its developments or trial and error behaviour to learn the consequences of certain actions. In system with highly developed cognitive abilities, thinking and reasoning are often appropriate means of acquiring new information about an uncertain domain of reality (ibid, p. 20).

On the other hand, when PSI is equipped with the need for certainty, life becomes more dangerous because exploration means exposure to unknown parts of the environment and exploration could also result pain and can even death. A falling degree of certainty results either in a higher tendency to flight behaviour or in behaviour patterns of specific exploration. In addition, when the fields of reality, which have been proven uncertain, are simply disregarded; this "withdrawal" from reality is also connected with the fact that PSI - at a falling degree of certainty - becomes more hesitant as far as its behaviour is concerned. Additionally, it does not take actions as fast as usual, its planning time is longer than other circumstances and it is not that "courageous" when it comes to exploration (for further details about the need for certainty and the need for efficiency signals see: (Dörner & Gerdes, 2005; Dörner, 2003; Dörner et al., 2002; Dörner, 1999; Dörner & Schaub, 1998; Dörner, 1997; Dörner & Hille, 1995).

4.2.5 Incompetence motive (the need for efficiency signals):

In the PSI-model, there is a variable "competence" which is dependent on the number of successes and failures and on the weights for the increment or decrement effects of successes or failures. If competence’s weight has a high value, a high increase in competence will result, even with moderate success. If competence’s weight has a low value, competence will not increase considerably even with great successes (Dörner, 2001).

The need for competence – the estimated degree of being able to cope with problems and the capability of coping with difficulties and problems (Dörner, 2003, p. 75)– is a need for “competence signals”. Each satisfaction of a need; for instance, the satisfaction of the need for water, is a signal of competence for PSI. Satisfaction of a need signifies that PSI is able to care for itself. Moreover, Need satisfaction serves as competence signal and enhances the activity of the “competence-neuron”, whereas non-satisfaction decreases this activity. On the other hand, a long lasting period of non-satisfaction signifies inability and; therefore, is an incompetence signal which empties the competence tank. Alternatively, when planning proves to be unsuccessful, PSI’s level of competence is endangered and PSI will exhibit the tendency to try its strength, and to prove its competence to itself. For instance, PSI will look for a task (which is difficult enough that mastery) that proves competence but not so difficult that the risk of failure is high. Therefore, A low level of competence (it shouldn’t be too low) will activate “adventure-seeking” (see: Bartl & Dörner, 1998, p.3).

Dörner (2003, pp. 76-77) has explained efficiency signal or what is called competence signals as the following:
“Generally spoken, each action which turns out to be effective (i.e., has an impact on the environment or even on the systems structure) is an efficiency-signal. If, for instance, the system is able to construct a plan for a course of actions, this plan is–before it is run–an internal change of the systems cognitive structure; planning has been effective and therefore results in an efficiency signal. If it turns out that an

action has no effect, it is an "inefficiency signal". An effect of an action can be an efficiency and an inefficiency signal at the same time. If there is an effect, but an unexpected one, this is an efficiency signal (as there is an effect) and an inefficiency signal (as an uncertainty signal always is an inefficiency signal too; a prediction has failed!). Obviously it is in the interests of an agent to strive for a high level of the certainty tank and of the competence tank too. A high level can be achieved by the above mentioned forms of behaviour and behavioural tendencies".

In PSI, competence determines, for instance, whether a risky course of action is chosen or abandoned. It determines also resolution level in planning and remembering and many other processes. There are two classes of competence seeking behaviour. The first class is tried to acquire new skills or new capabilities (physical or mental skills). An example for this form of behaviour is "diversive exploration" and this means an exposure to an unknown, even dangerous environment. The other class of competence seeking behaviour is more primitive. It is tried to find evidence for ones own competence by producing pure effects "which may be senseless in any other respect" (ibid, p.76).

4.3 PSI- Emotions

4.3.1 Introduction:

Emotional and motivational processes play a considerable role in human behaviour triggering cognitive processes (Bartl & Dörner, 1998, p.1). However, nobody knows what "emotion" is (Dörner, 2003, p. 75). Additionally, Emotions are different. First of all, it is not very clear what the concept of emotions means in psychology. For some scholars emotions are something like instincts and for others emotions are closely related to motivations (Dörner & Hille, 1995, p.3828). Dörner (2003) surveyed the literature underling emotion concept and he found that: there are many different definitions and meanings underling emotion concept such as empathy, sentimentality, motive, and intuition. Also, emotions have been defined as a sudden trouble transient agitation caused by an acute experience of fear, surprise, joy , or as mental feeling or affection (e.g. pain, desire, hope, etc.), or as distinct from cognitions or volitions. In addition, Emotion has been identified as a “mental state” or as a "pure somatic response" and there has been a long lasting, unsettled controversy about the relation of cognition and emotion.Dörner (2003, p. 75) noted that: “Under these circumstances trying to find out the "real" meaning of emotion does not make much sense, as there might be no "real" meaning at all. The words “emotion” or “feeling” have different meanings according to the context of their use (this is more the rule than the exception for words of colloquial language). So, it seems to be appropriate for scientific use not to look for a definition, but to fix one.”

Accordingly, Dörner (ibid, p. 75) described emotion as: “Emotion is a reaction of an agent, may it be man, animal or an artificial system, to two aspects of its relation to reality, namely to entropy or uncertainty of the environment and to competence”. The central mechanisms of emotion regulation in PSI are the motivators for certainty and competence, thus two informational needs. Active certainty or competence motivators elicit certain actions or increase the readiness for it. And because Dörner regards emotions as emergent phenomena which do not have to be integrated into a system as a separate module, emotions thus develop with PSI not in their own emotion module, but as a consequence of rule processes of a homoeostatic adjustment system. Afterward, Dörner proposed a theory of emotional reactions to understand emotions as reactions to the entropy of the environment and to the competence, which an agent has to cope with problems (Dörner, 2003, p. 75).

Dörner (see: Dörner & Hille, 1995, p.3828) believes that emotions should be considered as modulations of cognitive processes. That means emotions are not processes of their own, but the distinct forms which cognitive processes adapt under certain conditions. To have an emotion means that the processes of behaviour regulation are brought into a certain form according to the conditions of a situation. In PSI theory, emotion is basically considered as a sophisticated system which modulates the cognitive processes. Emotion determines whether behaviour is fast or slow, persevering or not, concentrated on the task or the environment, rough or fine (Dörner & Hille, 1995, p.3829). Hence, while there are numerous approaches to emotional concepts for software agents, the PSI-theory is unique in that emotions are not defined as explicit states but rather emerge from modulation of the information processing and action selection (Bach, 2002).

Dörner's agents indicate their reactions also by a number of graphical displays, including a face that is animated in accordance to the respective theory of emotion. Thus, it becomes possible to attribute mental states (specifically, emotional episodes) to the agent that allow for plausible explanation and prediction of its behavior (Bach, 2002). Bartl and Dörner (1998, p.7) stated that: "To be able to monitor PSI's emotions we gave a human face to PSI which alters according to PSI's emotional states. All these emotions are observable not only in PSI's facial expressions, but in its behaviour too." While Figure 4.5 shows some of the facial expression of PSI in different situations, figure 4.6 shows intensity of pain as an example of intensity degree of emotions.

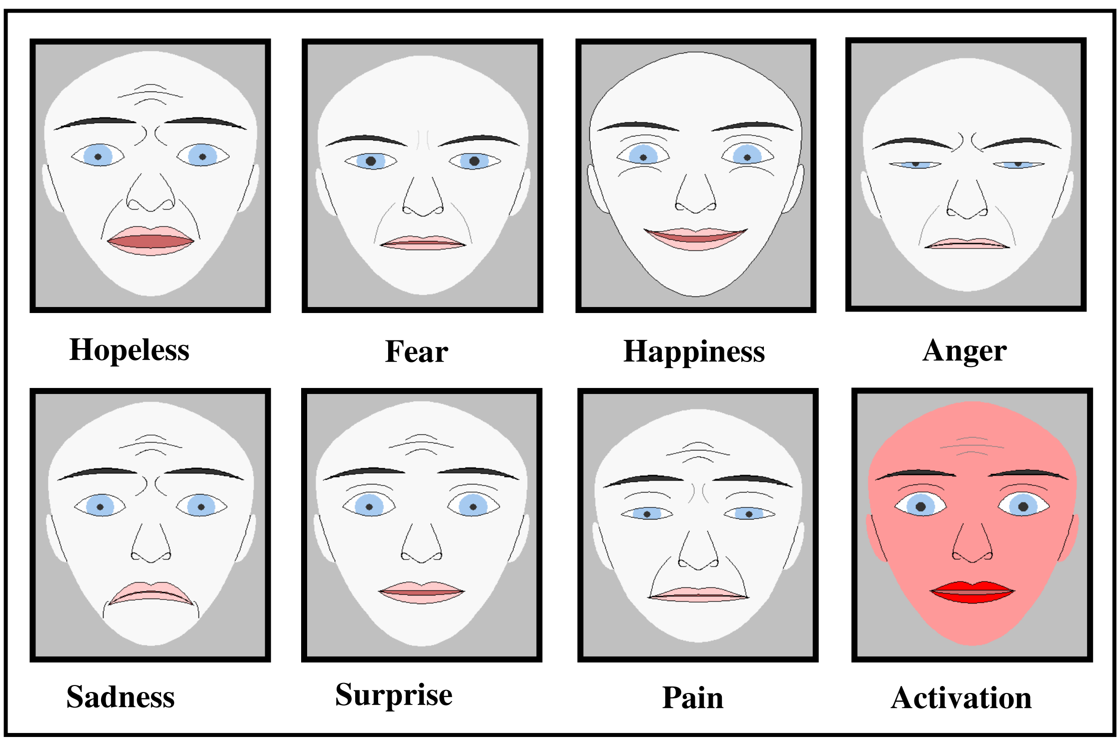

Figure 4.5: PSI's emotions.

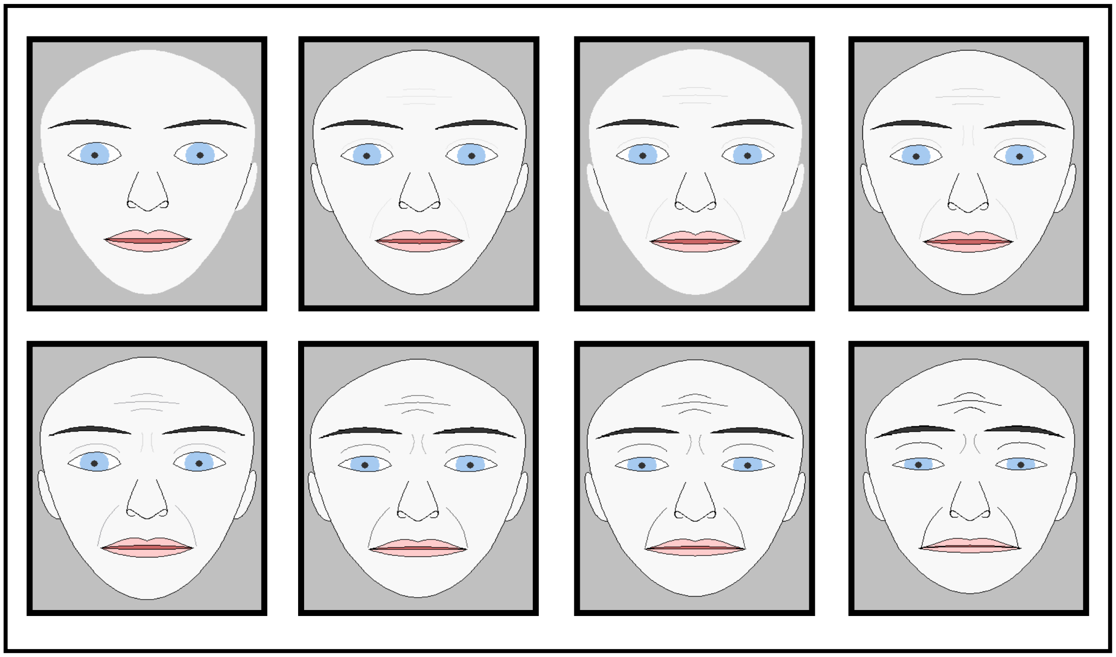

Figure 4.6: Intensity of Pain.

Bartl and Dörner (1998, p.1) explained the relationship between emotions and motivations as follow: “In a state of anger, thinking and reasoning differ from these processes under “normal” conditions. Different emotional states even influence perception in a specific manner. In a long lasting process of action regulation, when humans have to tackle difficult problems, neither emotions nor motives remain constant. Foreseeing that an important problem cannot be solved an individual will feel helpless and this feeling of helplessness will trigger other feelings and can change the current motive. The motive to find a solution for an intellectual task will be replaced by a motive to demonstrate “competence” as the inability to solve the problem threatens the self-confidence of the individual.”

As well, an uncertain environment normally provides difficult problems and therefore looks threatening and may generate anxiety or fear. But with a high degree of problem solving capabilities or a high degree of strength and skillfulness, an uncertain environment may look exciting, attractive and not at all threatening (Dörner, 2003, p. 75). Another instance, a sudden decrease of competence for instance would mean a sudden increase of arousal (arousal generally is a general preparedness for action), decrease of resolution level (to guarantee quick action), incomplete recall of possible modes of action for the situation at hand and rough planning of actions, hence swift and risky action. This mode of action could be described as anger (Dörner & Starker, 2004).

Moreover, Dörner and Hille (1995, p.3830) described the emotional behaviour of artificial agent (PSI-agent) that shows behavioral indicators for "fear", "hope", "anger", "resignation", "depression", and other emotions as the following:

« Imagine a dangerous situation. One gets a warning that something terrible will happen minutes later. Putting the artificial soul in such a situation, we observe an alteration of behavior. In the moment of noticing the signals of danger, the modulating parameters alter their values. The activation increases: the system accelerates the speed of information processing. The selection threshold increases rapidly: for another motive but avoiding the dangerous situation it becomes hard to get selected for giving the aim. The resolution level decreases rapidly: there is no time to explore, plan or act very carefully. The rate of updating the image of the environment decreases: all the resources are needed for the motive to avoid the danger. Later this rate increases again: updating the image of the actual situation becomes more and more important when approaching the danger, possibilities of escaping are viewed. We can observe a highly activation, the sticking on one motive, a rather rough way of thinking and doing, and no looking around in the beginning turned into a watching the actual situation. We find the artificial soul anxious. The dangerous situation doesn't happen. An all clear signal alters the values of the four modulating parameters again. They meet their normal levels."

Briefly, according to PSI-theory distinct emotions like fear or anger are not considered as separate modules of the psychic system but are supposed to be modulations of planning, perception and behaviour. Anger for example is defined by a superficial level of perception, high activation, high concentration and a low level of planning (Hoyer, 2003, p.263).

4.3.2 Selection threshold:

Because PSI's architecture allows several needs to be active at the same moment, it is therefore important to equip PSI with a selection device. This selection device has to select one of the active motives for execution. The motive selected will become the actual intention (Bartl & Dörner, 1998, p.4). On other words, since several motivators always compete with one another for the action control, the system has a motive selector that decides, with the help of a fast expectation value calculation, which motivator possesses the greatest motive strength and thus is to receive the advantage for execution and the selected motive will become the actual intention. The value of a motivator is determined by:

- Its importance (size of the deviation from the desired value).
- Its urgency (available time until the removal of the actual condition).
- Its expectation (expectancy-value), which is determined by the ability of the agent to actually satisfy this need (probability of success).

In addition, Selection threshold could also be called "level of concentration" (ibid). Selection threshold is the strength of defending the actual intention against competitors, against other intentions having the tendency to take over the command. The strength of the different motives is not at all constant in the life of PSI, but changes continuously. The needs for energy and for water continuously increase as they are consumed. But a motive can also gain strength by external factors: If for instance PSI notices in a certain situation that it would be easy to get water, a tendency to shift to the water-intention will result as now the expectancy value for the water-motive increased. Or if an unexpected event will occur the "need for certainty" might increase and PSI will exhibit the tendency to explore the (uncertain) environment or will have the tendency to run away and to hide. Or if for instance planning proves to be unsuccessful, PSI's "self-confidence" (level of competence) is endangered and PSI will exhibit the tendency to "try its strength", to prove its competence to itself, for instance by looking for a task which is difficult enough that mastery proves competence, but not so difficult that the risk of failure is high. If selection threshold is high “behavioural oscillations” (i.e., a rapid change between different intentions will be hindered to a certain degree). A high selection threshold prevents PSI on the other hand from using unexpectedly arising opportunities or from reacting to unexpected dangers. If selection threshold is high, the field of PSI’s perception will narrow down (ibid, pp.6-7). Furthermore, generally when the selection threshold is high, it is difficult for other motives to displace the current motive.

4.3.3 Resolution level:

Bartl and Dörner (1998, p.6) noted that: “Resolution level is the degree of exactness of comparisons between sensory schemata. Comparisons take a long time at a high level of resolution, but they will be reliable. Under high pressure (when activation is high) the resolution level is low, comparisons do not need a long time, but the risk of “over-inclusiveness” is high. A low level of exactness will lead to the tendency to consider unequal objects and situations as equal (This is due to certain mathematical reasons.)”

A low resolution level means rough planning, superficial ("over-inclusive") perception and shallow, conservative processes of recall (Dörner & Starker, 2004,). In other words, a low level will cause quick planning processes and a high readiness for action. Plans will be however rather risky (Bartl & Dörner, 1998, p.6). In addition, a high resolution level means roughly exploring, planning, and acting, a low resolution level influences exploring, planning, and acting so that it happens in a very careful way. For example, Dörner and Hille (1995, p.3829) noted that the modulating parameter resolution level is influenced by:

- ➔ The importance of the leading intention (based on the strength of the underlying need); the higher the importance of the intention, the higher the level of resolution (i.e., the more carefully is the exploration, the planning, and the acting concerning this intention).

➔ The urgency of the realization of the intention; the higher the urgency, the lower the level of resolution (i.e., the faster the intention can be realized, because it is urgent).

➔ The pressure of needs (based on the strength of all generated intentions); the higher the activation, the lower the level of resolution (i.e., the faster the intention can be realized, because there are a lot of other things to do).

4.3.4 Action regulation:

Dörner (2003, pp. 75-76) described the regulation of certainty and competence as follow (see also figure 4.7):

"For an agent it is sensible to adjust its behaviour to the uncertainty of the respective situation and to its competence. In an uncertain environment it is reasonable for instance to exhibit a high degree of:

- **Readiness to act:** As it is unknown, what would happen next. (this means for biological systems a high degree of general arousal, and this again means a high level of the sympathetic reaction, of muscle tension, of oxygen within the blood, etc...),
- **Safeguarding behaviour**: For instance a high degree of background monitoring,
- **Explorative behaviour:** (In order to discover the rules of the respective domain of reality and thus diminishing the entropy),
- **Aggressive tendencies: (**In order to destroy possibly threatening objects when flight is impossible or if it is unknown what to do else with the object),
- **Flight tendencies: (**In order to escape from circumstances one cannot cope with).

If competence is low, it is sensible to exhibit a high degree of:

- **Competence seeking behaviour:** There are two classes of competence seeking behaviour. Either it is tried to acquire new skills or new capabilities, be it physical or mental skills or capabilities. An example for this form of behaviour is "diversive exploration" (Berlyne, 1974) and this means an exposure to an unknown, even dangerous environment. — The other class of competence seeking behaviour is more primitive. It is tried to find evidence for ones own competence by producing pure effects (which may be senseless in any other respect). Vandalism may be understood as an example ofsuch a form of competence-proving activity.

- **Flight tendencies:** (In order to escape threats one cannot cope with).

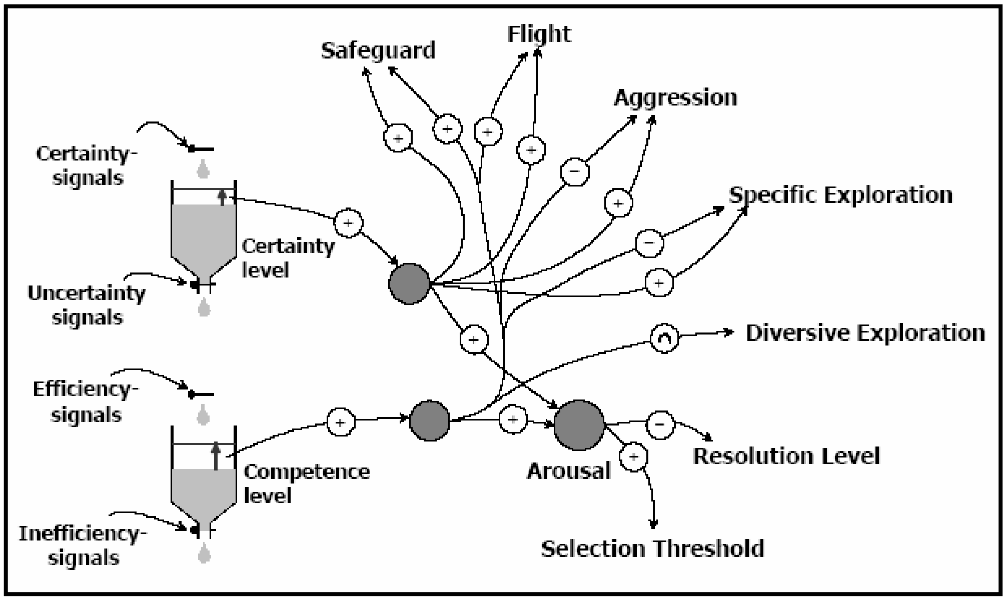

Figure 4.7: Competence and Certainty – Regulation.
Source: (Dörner, 2003, p. 76).

Moreover, Dörner (ibid, 77) explained that: “Obviously it is in the interests of an agent to strive for a high level of the certainty tank and of the competence tank too. In figure 4.7, you find a hypothesis about how a system may activate the respective forms of behaviour or behavioural tendencies.

1. When the level in the certainty tank is low (and hence entropy is high) the frequency of *safeguarding activities* should increase to preserve the system from surprises. — If however competence is high, the frequency of safeguarding activities should not be too high, as surprising events could be mastered.
2. When entropy is high (level in certainty tank low), *flight* and *aggressive* tendencies should be high, either to escape from threatenings or to destroy threatening objects. (Aggression – technically spoken – is an unspecific

measure to get rid of threats.) When competence is low, flight should be preferred to aggression if possible.

3. When competence is low tendencies for *diversive exploration* should be high, but not high if competence is too low, as diversive exploration always means exposure to uncertain situations and this means possible threatenings with which one should be able to cope.
4. When competence is low tendencies for *aggression* should be high, as aggression is an unspecific method of producing strong effects.
5. When competence and certainty is low, *arousal* should be high, as under these conditions readiness for quick action is necessary.
6. When readiness for quick action is necessary, the *resolution level* for cognitive processes should be low to waste no time. (When the time which cognitive processes consume is dependent on the magnitude of a fan of associations which are spreading from a starting point, a low resolution level could mean an inhibition of the spreading of activation in a neuronal network).
7. When readiness for quick action is necessary, the level of concentration on the active intention should be high and therefore possibility of distraction should be low. This could be achieved by setting a *selection threshold,* which a competing motive should pass before it takes over the guidance of behaviour, to a high value.

In addition, Bartl and Dörner (1998, pp.5-7) stated that: "The information processing of PSI is "modulated". This means that all cognitive processes of PSI are "shaped" according to certain conditions. Such conditions are for instance the strength of the actual intention, the overall amount of all the different needs, the amount of competence and others. These conditions set specific "modulators". One of these modulators is "activation" which depends on the strengths of the needs (roughly spoken the amount of activation represents the sum of the strengths of the needs). Activation triggers some other modulators, for instance "resolution level" and "selection threshold". These modulators (resolution level and selection threshold) together with the need for certainty and the need for competence produce a lot of "emotional" forms of behaviour. PSI exhibits fear (expectation of an uneasy event), anxiety ("need for certainty"), anger (when unexpectedly PSI is hindered to reach a goal), surprise (unexpected event). This theory of modulations together with the specific motivational structure of PSI constitutes a "sub-affective" theory of emotion."

Furthermore, Dörner and Hille (1995, pp.3828-3829) explained that:
"Anger, as an example of how emotions are modulations of the processes preparing and controlling behaviour could be described as characterized by:

- High activation (which means amongst other things a high speed of information processing).
- A high "selection threshold" (i.e., a high tendency to concentrate on the actual intention and a low sensibility for stimuli not concerning this intention).
- A low resolution level (i.e., a rather rough way of looking to the environment and of planning as well as decision making which does not take into account conditions for actions and side and long term effects in detail). A low level of resolution results thus in "unconditional" behaviour and "over-inclusive" planning.
- A low rate of updating the image of the actual situation. (Somebody who is angry does not take into account the details of the situation and its changes.)
- "Angry behavior" is different from "non-angry behavior" not because some independent state of "anger" is present or not, but because parameters like "selection threshold", "resolution level", "activation", and "rate of updating" have got different values.

These specific levels of the modulating parameters guarantee an appropriate behaviour in the current situation. In the situation triggering anger it is most of the time appropriate to be fast (high activation), to be persevering (high threshold of selection), to be rough behavioring (low level of resolution), and to be concentrated on the source of anger and its coping instead of watching other details of the environment (a low rate of updating), so to say: it is appropriate to be angry (ibid).

4.4 Related Work

4.4.1 Introduction:

In a series of experiments Dörner and his co-work examined the relation of the PSI-model to human behaviour. Different forms of a complex, dynamic, maze-like environment were used where human subjects had to play a kind of adventure game. We will review some of these experiments and their results as follow:

4.4.2 Research one: Single PSI and societies of PSIs.

Aims: Dörner (1997, pp.17-22) has designed this research to investigate the following aims:

1. To investigate the behaviour of single PSI and societies of PSIs when exposed to an environment that provides food and fuel, but on the other hand can be dangerous for the health and even the life of a PSI.
2. To investigate the role of emotions for behaviour and action regulation by investigating the behaviour of an artificial system.

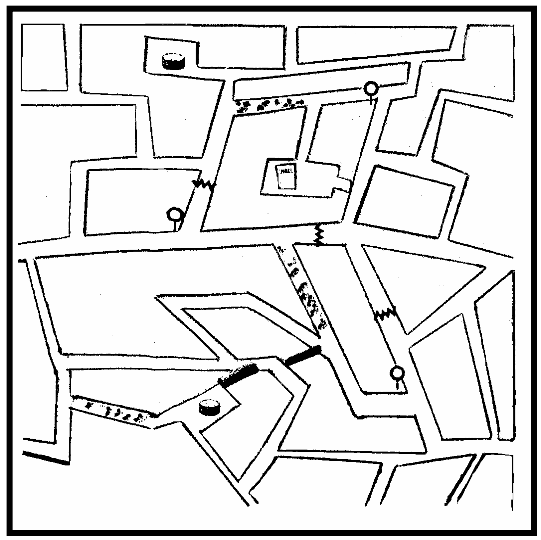

Figure 4.8: The World of PSI. Source: (Dörner (1997).

Procedure: PSI lived together with other similar systems in a mazelike environment, where it could find at several places petrol stations and wells to satisfy its basic needs for fuel and water as shown in figure 4.8. The 'World' of PSI looked like the map of a town. This 'World' however was not stable, but the conditions for action change more or less quickly. Some of the roads were barred and could not be penetrated. But PSI can learn to identify indicators for such states of a road and in this way may be able to avoid unnecessary detours. Additionally, some thoroughfares could only be passed at certain daytimes and the PSIs have to learn this too. The roads may be sometimes in bad conditions and therefore provide pains for PSI when passing through. These roads were dangerous for the axes and could cause serious damages. Therefore it was wise to avoid such roads and to make detours.

Results: Single PSI and societies of PSIs that lived in a rather complex and dangerous environment and equipped or not equipped with a need for affiliation were experimented. Results showed that when PSI exposed to a new environment and forced to live in it without the help of other PSIs, single PSI had difficulties to survive in such complex environment. PSI would have died because of a lack of water and fuel in the first phases of its existence. But when PSI lived in PSIs society with an affiliation motives, its behaviour were much better because PSI got help from other PSIs. Additionally, it was remarkable that when PSI lived in PSIs societies with an affiliation motive learn quickly as the PSIs in the PSIs societies without an affiliation motive because of knowledge development in the PSI's memory.

4.4.3 Research two: PSI- model with and without social motive.

Aim: This experiment was conducted within the socionics-project (Detje, 2003, pp.243-244) and aimed to answer the following question: "How would PSI's behaviour change if a social motive is added to PSI?"

Procedure: Island game version-II was used to investigate the aim of the study (see figure 4.9). Moreover, the social motive that was implemented in PSI was a need for affiliation, implemented as a need for signals of legitimacy. PSI could send and perceive signals of legitimacy (L-signals) and signals of anti-legitimacy (AL-signals). To simulate social agents, an object called "Teddy" was created that could send signals of

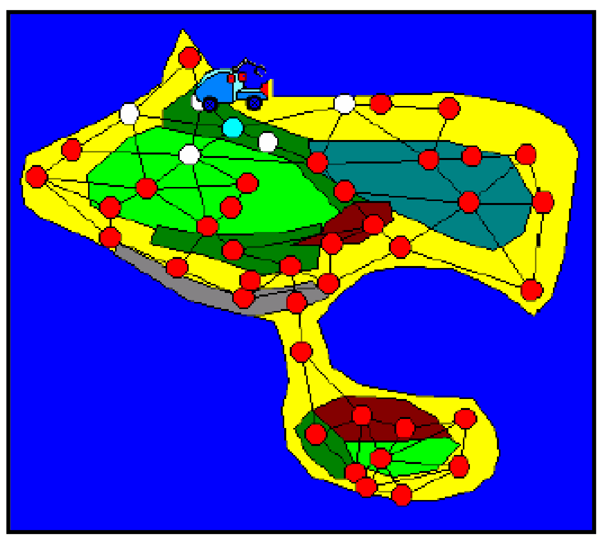

Figure 4.9: Screenshot of the island-II. Source: (Detje & Kuenzel, 2003, p. 317).

legitimacy if it was "manipulated" in the "right" way. New operator was given to PSI (the "kiss"-operator) that allowed manipulation of the Teddy-object to send the signals needed to satisfy the motive. Table 4.1 shows the definition for the PSI-program.

Teddy	**mX**	**Teddy F**	**Affiliation**	**-1**	**Kiss**
Teddy	**mC**	**Teddy F**	**Affiliation**	**0.1**	**Hammer**

Table 4.1 : Signals of Legitimacy and Anti-Legitimacy.
Source: (Detje, 2003, p. 243).

If operators "mX" (= kiss) or "mC" (= hammer) are applied to the object "Teddy" this object is transformed into "TeddyF" and the need for affiliation is changed ("-1" = satisfied completely; "0.1" = little increasing) (ibid, p. 243).

Results:

1- PSIs that could also perceive signals of anti-legitimacy (AL) behave slightly different compared to PSIs that could only perceive signals of legitimacy (control). These differences resulted in a higher amount of break-downs, a lower amount of unsuccessful manipulations and different action regulatory priorities.

2- The PSIs did not differ in "handling" their hunger, thirst, collection of items and damage, but they did differ with respect to the needs for certainty, competence and affiliation. These results indicated that the change only affects the regulation of affiliation and its side effects in terms of a lower level of certainty and competence.

3- To see if the lower amount of unsuccessful manipulations was really due to the avoidance of the new combination of hammering the "Teddy"-object (which increases the need for affiliation and thus should be avoided), a closer look at the first PSI of each group (n=30) and compared the unsuccessful manipulations for each operator was considered. The results indicated that the control-PSI was much more likely to perform unsuccessful attempts to hammer objects.

4- A closer look at PSI's specific behaviour towards the Teddy-object indicated that some AL-PSIs seem to suffer from "social masochism".

4.4.4 Research three: A comparison between PSI-model and human behaviour in a complex and dynamic task.

Aims: Bartl and Dörner (1998) aimed to evaluate the ability of PSI-model to model human behaviour in a complex and dynamic task (the BioLab game). A comparison between the performance of the model and the performance of the subjects was measured. These evaluations included comparisons of emotional reactions in "critical situations" and of the process of adapting the behaviour to environmental changes. Furthermore, single cases were analyzed to validate the assumptions of the model about the interaction of motivation, cognition and emotion.

Procedure: In the BioLab factory, the "biological laboratory of sugar-beet-based energy production", subjects were asked to produce certain types of molasses in order to generate electricity and heat (see figure 4.10). There are 10 different kinds of catalysts to modify the molecular structure of the molasses. The subjects, as well as, PSIs had to fulfill three aims. Two appetitive aims that were the production of electricity and heat, and one aversive aim (the avoidance of contamination). Two important aspects of the task must be mentioned:

1- The subjects did not know anything about the structure of the system. They had to explore it.

2- As well as the PSIs, they had to deal with an environment completely new to them. Furthermore the situations of need satisfaction got exhausted after they had been frequented several times.

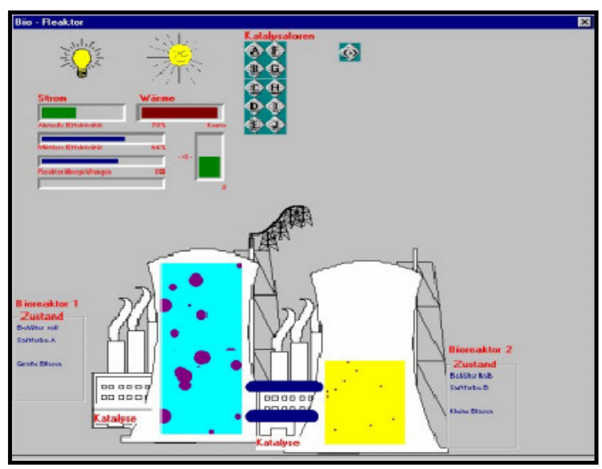

Figure 4.10: Screenshot of the program surface of the BioLab game.
Source: (Bartl & Dörner, 1998, p. 8).

Experimental Design: The experiment conducted with 19 subjects (12 female and 7 male) each of them playing the BioLab game for one hour. The age of the subjects varied between 19 and 29 years with a mean of 25 years. The sample of subject was compared to a sample of PSIs. 19 model runs were produced by varying starting parameters by chance within a certain range. The sample of artificial subjects mainly varied as to memory capacity and depth of planning. In order to have fair conditions comparing the performance, the PSI protocols were cut off as to the mean number of actions carried out by the subjects during one hour.

Results: The data analysis concentrated on two aspects: one of them was the performance of human and artificial behaviour. The general aim of the BioLab game was to satisfy three system needs: the need for electricity, the need for heat and the avoidance of contamination. Fulfilling these needs would be a valid indicator for their efficiency working on the BioLab problem. However, comparing the efficiency was not sufficient, because similar efficiencies could be achieved by different behaviour. The second aspect of data analysis focused on behavioural aspects, such as the percentage of effective actions and the pattern of catalyst use.

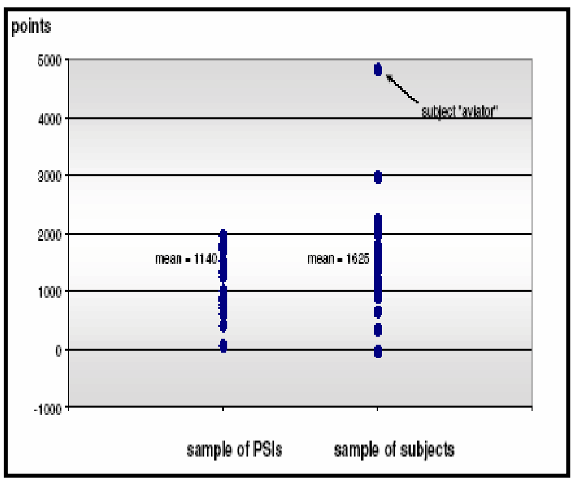

Figure 4.11: Efficiency of need satisfaction. Source: (Bartl and Dörner, 1998, p. 11).

The markers symbolise single subjects as to the number of points achieved in the BioLab game (ibid, p. 11).

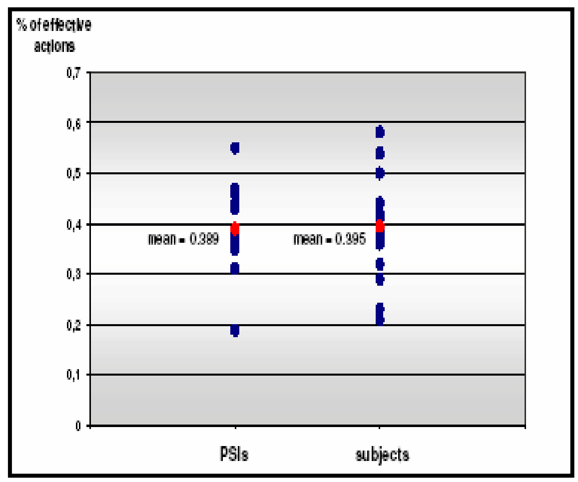

Figure 4.12: Percentage of effective actions. Source: (Bartl and Dörner, 1998, p. 11).

The markers are set for each single subject (ibid, p. 11).

Efficiency of needs satisfaction: The efficiency of managing the BioLab problem was represented by the score achieved at the end of the run. Figure 4.11 shows that, in general, the subjects as well as the model runs were quite successful in managing the BioLab problem. The two groups do not differ significantly in the t-test for independent samples.

Effective actions: Managing the BioLab problem subjects had to learn the specific effects of catalysts. Some catalysts were always effective; others need certain conditions to work. Comparing the percentage of effective actions between the subjects and the model runs were striking. The two samples had similar means and comparable variances (see figure 4.11).

General discussion of the results:

1- The behaviour of PSI and human behaviour were remarkable parallel.

2- The performance of extraordinary successful subjects could not be achieved by PSI, because humans more or less frequently change their thinking and planning procedures. PSI was not able to do so, because mainly language* and self-reflection was missing.

3- Generally, "emotional" systems were more successful than unemotional ones.

4.4.5 Research four: PSI-model with and without emotions.

Aim: In particular, whether emotions are helpful or even necessary for problem solving or not was investigated in this study by Dörner and Starker (2004). They had investigated the behaviour of a PSI-model with and without emotions.

Procedure: To examine the role of emotions, Dörner and Starker compared (20) PSI-subjects with different "personalities" with (20) PSI-subjects with fixed parameters for arousal and resolution level" on a medium level.

Results: Dörner and Starker found that there were highly significant differences in respect of the behavioural parameters of the two groups. The emotional PSIs were more successful in collecting nucleos and in preserving themselves from damage than non-emotional PSIs, as shown in figures 4.13 and 4.14. The "emotional" system was more able to adjust its behaviour to the requirements of the situation in respect of uncertainty and incompetence motives than the non-emotional system.

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* This problem (language) was partly solved by implementing language in PSI-system. For further details see: (Dörner, 1999; Künzel, 2003; Künzel, 2004).

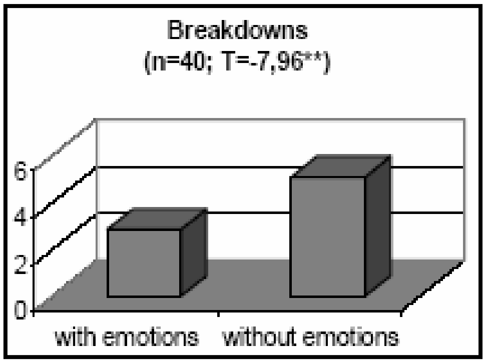


Figure 4.13:
Mean number of breakdowns.

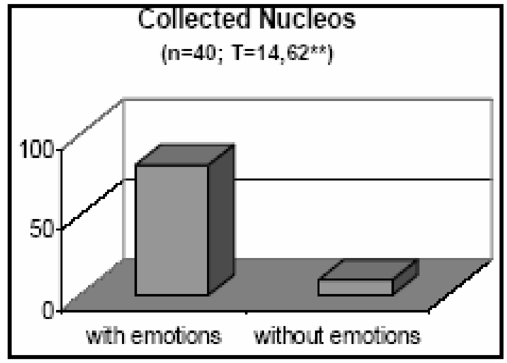


Figure 4.14:
Mean number of collected nucleos.

Source: (Dörner and Starker, 2004).

4.4.6 Research five: A comparison between PSI-emotions and human emotions in a complex and dynamic task.

Aim: In this research, Dörner (2003) investigated and compared the artificial emotions that were implemented in PSI-agent with the human emotional system. The variance of the reaction time was used to measure the emotional behaviour of the subjects because it was supposed that emotional regulations resulted in variations of reaction times.

Procedure: The overall characteristics of behaviour in longer sequences of behavioural units were observed in the island game.

Simulation and results:

1- Figure 4.15 shows a pattern of the reaction times of a subject (III in the island game) for a 30 minutes period at the beginning of the game. The different colours belong to different forms of action. The light grey lines stand for manipulations of objects, shaking them, hammering them etc.. The medium grey lines stand for locomotions from one station to another one or for trials of locomotions. This subject (III) was rated by the experimenters as "very emotional".

2- Figure 4.16 shows the reaction pattern of a simulated "emotional" subject. A high level of emotionality was simulated by giving the arousal formula a high increment weight so that arousal increased very quickly with increasing values of the motives. Dörner (ibid) explained that the overall pattern of this simulated subject was similar to the pattern of subject III.

3- Figure 4.17 shows a pattern of the reaction times of a subject (XXXIX), who was rated as "cool". Subject (XXXIX) had showed longer periods of being occupied with one object (systematic exploration of an object to find out what could be done with it can be observed in the phases around 100 and 400) and longer periods of locomotions (diversive exploration of the island), indicators of a more "organized", sustained behaviour.

4- Figure 4.18 shows the reaction pattern of a simulated "cool" subject. The results of this research showed that it seemed to be possible to generate patterns of emotional behaviour similar to the patterns of human behaviour. By varying the PSI- parameters, one can get different types of personality and make predictions of the behaviour of individual subjects.

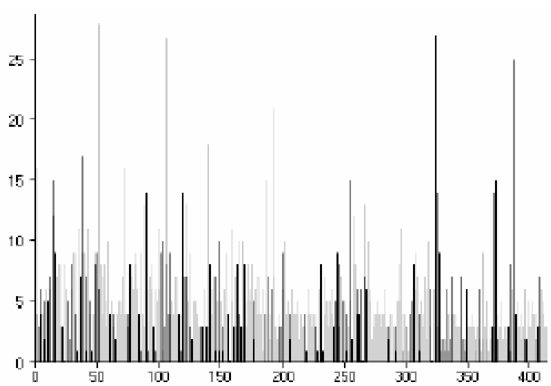


Figure 4.15: An "emotional" subject.

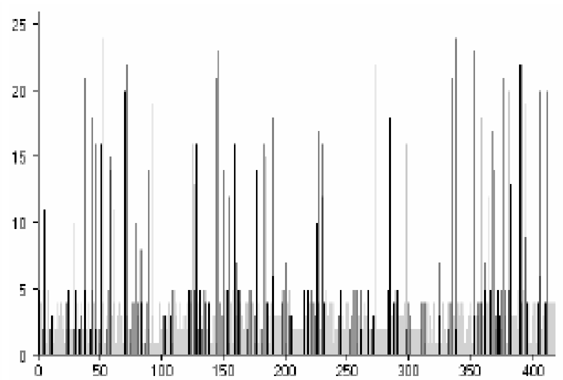


Figure 4.16: A simulated "emotional" subject.

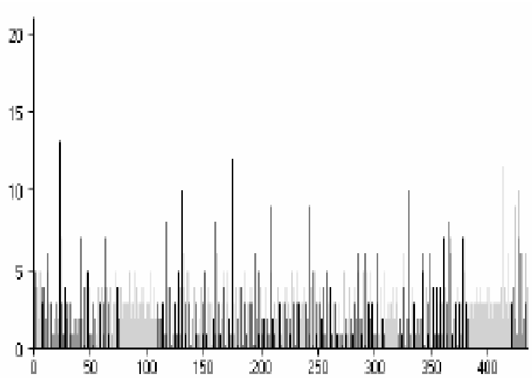


Figure 4.17: A "cool" subject.

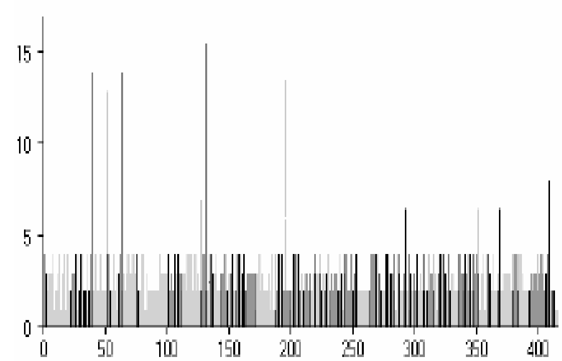


Figure 4.18: A simulated "cool" subject.

Source: (Dörner, 2003, p. 79).

4.4.7 Research six: Simulating social emotions, especially for aggression in groups of social agents.

Aims: In this research, Dörner (2005, pp.39-43) aimed to simulate social emotions, especially for aggression in groups of social agents.

Procedure: Dörner constructed emotional agents according to the Psi-Theory, but had only rather reduced cognitive capabilities compared with the original Psi-agent. He called this agent a "Psi-mouse". Figure 4.19 shows some mice in their environment and the cognitive map of one mouse for a distinct area. The memory of a mouse consists of cognitive maps and includes a "social memory" too (the mice remember "friends" and "enemies"). Dark-gray spots in figure 4.19 are water places (W), food-places (F), dangerous areas (D); here the mice can be hurt. If they are hurt they can try to find a healing – place (H).

Basic concepts: Dörner (ibid, p. 41) explained aggression and crowding as follow:

Aggression: To be aggressive is not at all based in the motivational system of the mice. To destroy something or to bite another mouse is just an instrument among others and not in any way distinct. On the contrary, there is an inbuilt avoidance tendency of the mice to bite each other, especially not to bite friends.

Crowding: Crowding means an increase in aggressive actions when a population increases.

Results of the simulation:

1- Figure 4.20 shows that when there were only a few mice in the region, each mouse had a lot of friends and not very many enemies. This changed when the populations grow. It can be seen that the relative number of friendships decreased and the number of enemies increased (the development of friendships and enmities was according to the crowding).

2- Figure 4.21 shows the rate of aggressive actions in a population of mice living in a very poor environment where it was hard to get food or water. These mice were very aggressive. The average level of hunger and the average level of thirst were very high. But the level of the competence motivation was rather low. This was due to the fact that these mice experienced their aggressiveness as a satisfaction of the need for competence.

3- Figure 4.22 shows results of a similar population of mice living in a comparably rich environment. Here, the aggression rate was rather low and the level of hunger and thirst was low too, as these mice found enough opportunities for feeding and drinking. It was for them not necessary to fight for food. So the level of the need for competence was rather high; these mice did not get very much efficiency-signals, as getting food and water did not need much effort and hence aggression was not necessary.

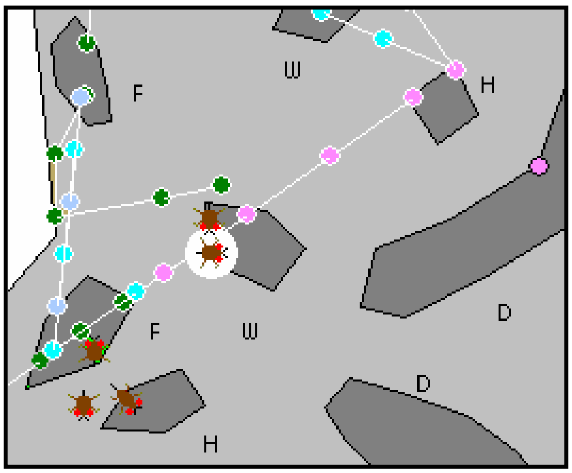


Figure 4.19: Some mice in their environment. Source: (Dörner & Gerdes, 2005, P. 41).

Mice in between food – and water places and with paths leading to different goals for the selected mouse "white halo" (ibid, P. 41).

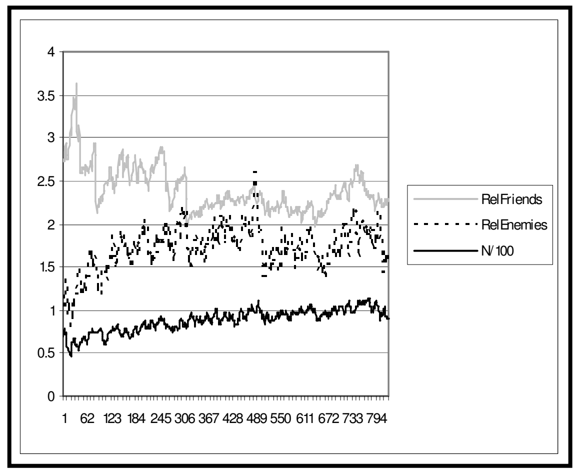


Figure 4.20: Growth of a population and development of the numbers of friendships and enmities.

Source: (Dörner & Gerdes, 2005, P. 41).

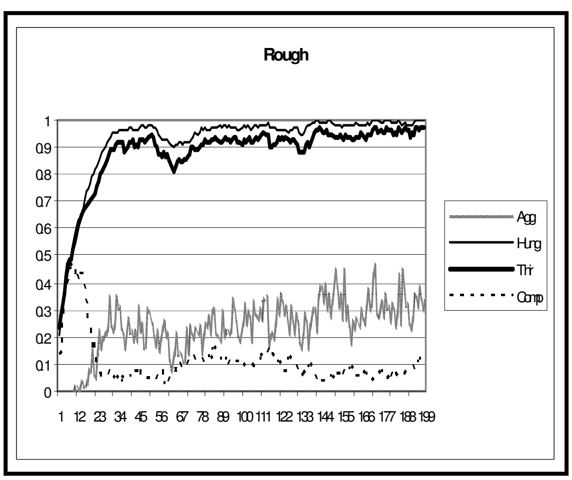


Figure 4.21: Rough environment, aggression and competence.

Source: (Dörner & Gerdes, 2005, P. 42).

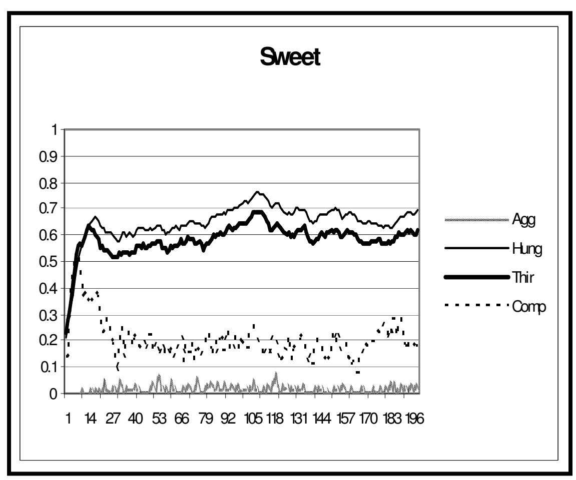


Figure 4.22: Easy environment with enough food, water, etc..

Source: (Dörner & Gerdes, 2005, P. 42).

Discussion

In this chapter, we have aimed to give a general introduction and a big picture of the scope of the PSI-theory within the artificial intelligence and computer science communities. This scoping is useful to understand human action regulation. Hence, we have demonstrated a general description and basic fundamentals of PSI-theory that was partially implemented as a computer program. To support these aims, we have discussed "intention" that was considering the core of PSI-theory and control the action of PSI-agent.

For a good overview of the process of running intentions, we have seen that it included firstly a level of automatic functioning, then a level of internal planning, and finally a level of active exploration. Careful consideration was given to PSI- motivators that consisted of existential needs (without these needs PSI-agent could not survive) and informational needs (certainty - competence – affiliation). It is pretty clear that affiliation motive is the need for social contacts and group integration. The PSIs were stimulated to form groups and to help each other as it was shown by (Dörner, 1997, pp.17-22; Detje, 2003, pp.243-244; Dörner, 2005, pp.39-43). Related to Dörner research (1997), when PSI exposed to a new environment and forced to live in it without the help of other PSIs, single PSI had difficulties to survive in such complex environment.

We have also demonstrated the key element to explore the surroundings; uncertainty motive. In fact, uncertainty motive, from a conceptual standpoint, is generally a need of information that is satisfied by "certainty signals". The interactions between uncertainty motive and incompetence motive (which is dependent on the number of successes and failures) affect PSI- emotions. This point of view had been admitted by Dörner and Hille (1995, p.3828) as they had mentioned that "emotions are not processes of their own, but the distinct forms which cognitive processes adapt under certain conditions."

Taking this view, Bartl and Dörner (1998) had found that "emotional" systems were more successful than unemotional ones. This result holds a possible key to simultaneously investigate and compare the behaviour of a PSI-model with and without emotions. The most unique result of Dörner and Starker (2004) was that the emotional system was more able to adjust its behaviour to the requirements of the situation with respect to uncertainty and competence than the non-emotional system. Selection threshold as a device that has to select one of the active motives for execution depending on its importance, its urgency and its expectation (probability of success) was discussed in this chapter followed by further details about resolution level concept that was defined by Bartl and Dörner (1998) as the degree of exactness of comparisons between sensory schemata depending on the importance and the urgency of the leading intention.

These concepts of PSI-theory explained human action regulation through the relationships between cognition, emotion, and motivation. Hence, PSI- theory can explain behaviours such as, readiness to act, safeguarding behaviour, explorative behaviour, aggressive tendencies, flight tendencies, and competence seeking behaviour. Researches done in the scope of PSI-theory indicated that PSI can simulate human behaviour in complex and dynamic tasks. For instance, according to Dörner (2005), the effect of crowding relatively decreased the number of friendships and the number of enemies increased.

As said by Dörner (ibid), comparing to a population of mice living in rich environment, the PSIs' behaviours were aggressive when PSIs were living in a very poor environment where it was hard to get food or water. Additionally, Bartl and Dörner (1998) modeled human behaviour in a complex and dynamic task (the BioLab game).

The performance of the PSI was compared to the performance of human subjects and results of this comparison showed that the behaviour of PSI and human behaviour were remarkable parallel. Moreover, Dörner (2003) proved that PSI can simulate both "emotional" and "cool" subjects, and by varying the PSI- parameters, one can get different types of personality and make predictions of the behaviour of individual subjects.

The progress that was done and the further development of PSI-theory facilitate the responsibility to simulate different human action strategies and single cases too, as it will be explained in chapter five and chapter six.

Chapter

5

Research Methodology

The Experiment & Strategies

Summary

This chapter provides details about a method that has been used towards determining and classifying human action strategies in a complex and dynamic task. In section 5.1, we will provide a description of the experimental setup (i.e., participants, materials, island-game, apparatus, instructions, experimental design and procedure, and dependent variables) that has been conducted to investigate the main aim of the current research. Results of the experiment will be illustrated and discussed in section 5.2. As well, in section 5.3, we are going to describe the method and the major terms such as, strategy and tactics that will be frequently used when we analyze participants' action strategies. While a description of nucleotides-first-strategy (e.g., tactic towards satisfying uncertainty motive, incompetence motive, resolution level and selection threshold) will be explained in section 5.4, a description of balance between motives-strategy will be shown in section 5.5. In sections 5.6 and 5.7 we will discuss two different action strategies of two single cases.

5.1 The Experiment

5.1.1 Introduction:

The primary purpose of this research is to simulate different human action strategies in a complex and dynamic task. In this chapter, we will identify these strategies. To reach this goal; identifying different human action strategies, we have conducted an experiment that included a complex and dynamic task to figure out and investigate human action strategies. Island game-task has used to achieve this aim. Early versions of island game has been used as we had mentioned in chapter four to compare human behaviour with PSI's behaviour in the same complex environment and to investigate hypotheses about the interrelation between human behaviour and PSI-parameters. As well as, the island game has been used to test the hypotheses of the present research. In this experiment, our aim was to find answers to the following research questions:

- What are the different kinds of action-strategies will be used by the participants during playing the game?
- What are the differences between these strategies?
- What are the criteria used for choosing one's strategy?
- What are the effects (advantages and disadvantages) of one's strategy?
- What is the main goal of each strategy?
- Which possible courses of action can be taken under each strategy? and why?
- How the decision making will be taken?

Of course, we had also other many questions, but we just introduced the main categories of our questions.

5.1.2 Participants:

A sample of 40 participants (average age= 23,05 years and SD= 4,22), most of the participants were students at Otto Friedrich university-Bamberg, took the experiment in partial fulfillment of course requirements. All participants reported having no problem related to colour perception, and had normal or corrected-to normal visual acuity. All the participants had a basic familiarity with computers and were able to use the mouse.

5.1.3 Materials:

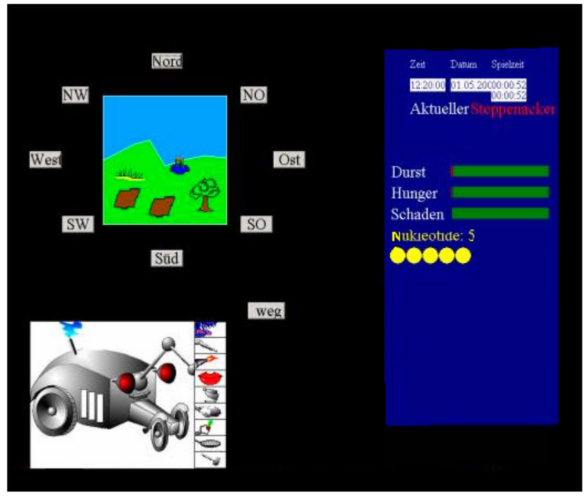


Figure 5.1: Screenshot of island-game.

Island game, a well-structured problem, was written using Pascal language. The internal game objects were organized for fast display of a scene and relied on the human visual system to pick out relevant objects and their relations. The program recorded each participant moves in the game accompanied with the associated time. The participants had to choose one operator from operators list, and then click by using the mouse to make the operator active to use. Figure 5.1 shows screenshot of island-game. In the following, we will discuss this game.

5.1.4 Island-game:

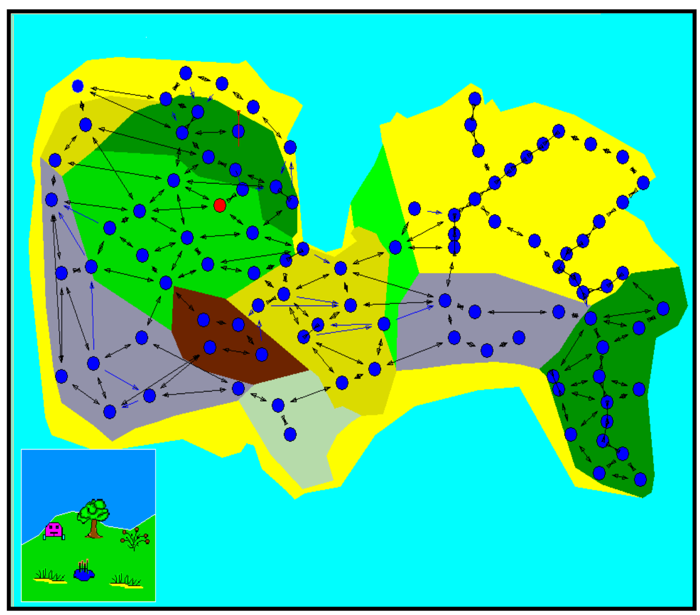


Figure 5.2: Locomotions and geographical structure of the island-game.

Island game*, a computer simulation of a robot - called “James”- endowed with several needs (e.g., energy and water), was used to investigate what “Dietrich Dörner” calls action-regulation. The island-game contains numerous locations as shown in figure 5.2.

* Island game –version III that had been used in the experiment was programmed by Frand Detje and Roman Seidl. For further details about the island-game program see: (Detje, 1998; Gerdes & Dörner, 2003).

In addition, there are many different objects that can be manipulated in various ways. Manipulations of the objects can have effects on the robot (for example, water can be drunk and the need for water is satisfied) or the environment (for instance, dunes can be sifted). Subjects have to control the robot to collect rocks called 'Nucleotides' and satisfy its existential needs. Moreover, they have to protect the robot from damage. Two explicit goals must be met to play this “island-game” successfully: **I**- The needs of the robot have to be satisfied and; **II-** The task of collecting “nucleotides” has to be fulfilled. Implicitly, and this leads to a third goal; **III-** The island, which is unknown to the subjects, has to be explored (see: Detje, 2003, p.243).

5.1.5 Apparatus:

The game was presented on a computer run with Windows 2000 (German version). Participants were seated approximately 60 cm from the 17 inch colour screen. Our experiment was videoed. Moreover, software packages that records participant’ responses have been developed, because measurement of responses on each session is strongly facilitating analyzing the data. So, responses were recorded with its input sensitivity. The program recorded each mouse click with its associated time accompanied by its topic (e.g., object, operator, direction,…etc.).

5.1.6 Instructions:

At the beginning of the experiment, participants were informed that they took part in a problem-solving experiment. Before beginning the first session, standard instructions for the task were given using Power Point presentation (see appendix) that was edited by Elkady & Seidl (2001). Instructions explained the basic rules of the game, described the task, and showed how to activate the operators. Furthermore, the instructions contained briefly description of the robot, the island environment, and the desirable tasks that are to keep the robot alive (e.g. to find enough water and food for the robot) and to collect so-called “Nucleotides”. It was also allowed to ask questions about unclear instructions to be sure that the participants were able to manipulate simply the simulation. During playing sessions, participants were allowed to think and speak freely.

5.1.7 Experimental design and procedure:

The sample of experiment was divided into two groups (group-A and group-B). Each group consisted of twenty participants. While “group-A” played island-game that its resources could be renewable, group-B played non-renewable resources version. All participants were tested individually in a quiet laboratory and in a sound-attenuated cabin that separated the participants from the laboratory. This was done so that the participants could only see the flat-screen monitor and minimize any effects that may be caused during the experiment. The participants were also asked to adjust the height of the chair that they were seated in so that they were approximately at eye level with the monitor. There was one video camera set in front of the participant to record the game and facial expressions.

To run effectively the software, the experiment was designed so that the experimenter could operate the game from the laboratory and the response to the game by using the mouse. The cabin allowed the experimenter to remain out of sight while the participant was interacting with the game. The software also recorded time for each mouse click so that the data could later be accurately analyzed. Participants completed the game in four consequent playing sessions. Each session is thirty minutes in duration. In order to minimize fatigue during sessions, between five and ten minutes break was given to each participant after completing thirty minutes of playing the simulation game. No feedback was provided by the observers to the participants about their performance in break periods. The simulation was adaptive to stop automatically every thirty minutes without losing the previously data. Therefore, the participant can safely complete the game from the point, which he/ she was stopped. As soon as the responses for a current session had been recorded, the next session began after the participant clicked the enter key. The entire experiment for each participant took approximately between 165 and 180 minutes. Two observers were seated in a well-illuminated laboratory facing 56 inch TV connected to camera in cabin that displayed the performance of the participant.

5.1.8 Dependent variables:

Basic dependent variables of the game were the achievement of both criteria (caring about existential needs and collecting "nucleotides"). Moreover, Dörner (see: Dörner & starker, 2004) determined eight systematic dependent variables that could summarize a participant's results of the island-game. Definitions of these dependent variables are shown in table 5.1.

NSL	Number of Successful Locomotions on the island.
NUL	Number of Unsuccessful Locomotions or trials to move on the island.
NLOC	Number of visited locomotions on the island (exploration activity).
NEX	Number of breakdowns of the robot because of missing "food" or water or too much damage.
NAGG	Number of approaches (aggressions) to an object (i.e., hazelnut bush, rock, etc.).
NSM	Number of Successfully Manipulated objects.
NUM	Number of Unsuccessfully Manipulated objects.
NNUK	Number of found Nucleotides.

Table 5.1: Definitions of the dependent variables.
Source: (Dörner & Starker, 2004).

5.2 Results of the experiment

5.2.1 Introduction:

In this section, we are going to show the results of the two experimental groups (group-A and group-B), and also the results of the whole sample on the eight dependent variables. Table 5.3, figure 5.6 and figure 5.7 show result of group-A (n=20). Table 5.4, figure 5.8 and figure 5.9 how results of group-B (n=20). As well, table 5.2, figure 5.4 and figure 5.5 show result of the whole sample (n=40). For further comparison, figure 5.3 shows means of group-A, group-B and the whole sample.

	NSL	NUL	NLOC	NEX	NAGG	NSM	NUM	NNUK
Maximum	399	667	95	14	402	694	1029	161
Minimum	139	136	37	0	183	155	95	23
Mean	268.75	353	65.2	6.33	281.15	316.13	289.1	83.4
SD	69.89	101.76	14.24	3.5	46.96	87.83	176.63	25.07

Table 5.2: Results of the sample (n= 40).

	NSL	NUL	NLOC	NEX	NAGG	NSM	NUM	NNUK
Maximum	399	479	75	11	402	390	535	105
Minimum	200	198	48	0	228	169	100	40
Mean	266.85	351.05	64.45	4.45	292.4	319.15	277.45	81.95
SD	53.49	63.75	7.32	2.21	32	42.71	90.45	15.05

Table 5.3: Results of group-A (n= 20).

	NSL	NUL	NLOC	NEX	NAGG	NSM	NUM	NNUK
Maximum	397	667	95	14	386	694	1029	161
Minimum	139	136	37	3	183	155	95	23
Mean	270.65	354.95	65.95	8.2	269.9	313.1	300.75	84.85
SD	61.98	93.01	15.95	2.5	37.99	76.02	156.6	24.53

Table 5.4: Results of group-B (n= 20).

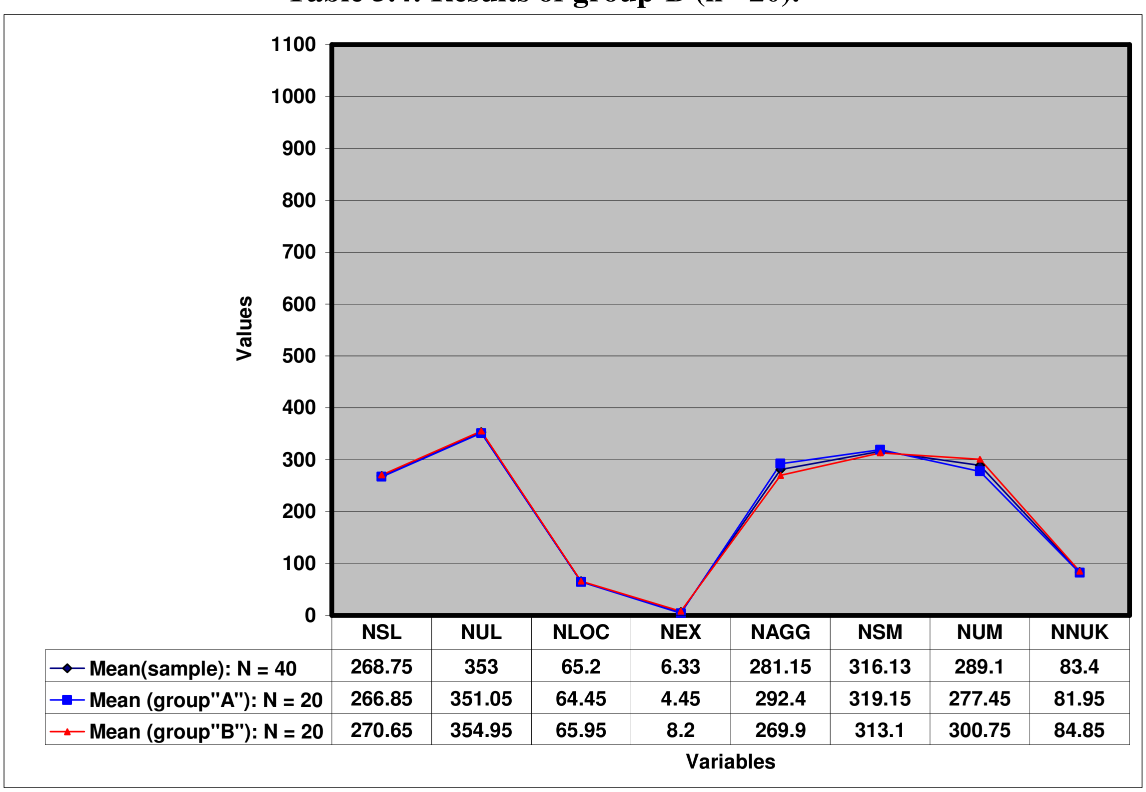


Figure 5.3: Results of group-A, group-B and the sample.

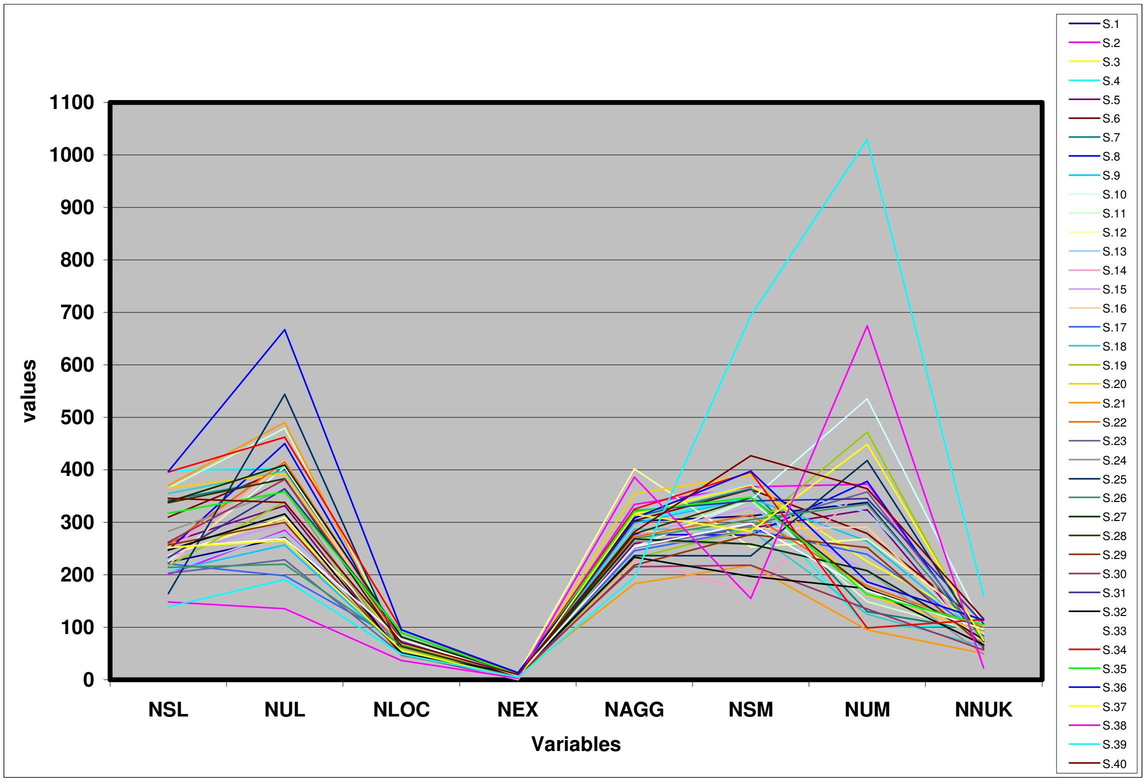


Figure 5.4: Results of the sample (n= 40).

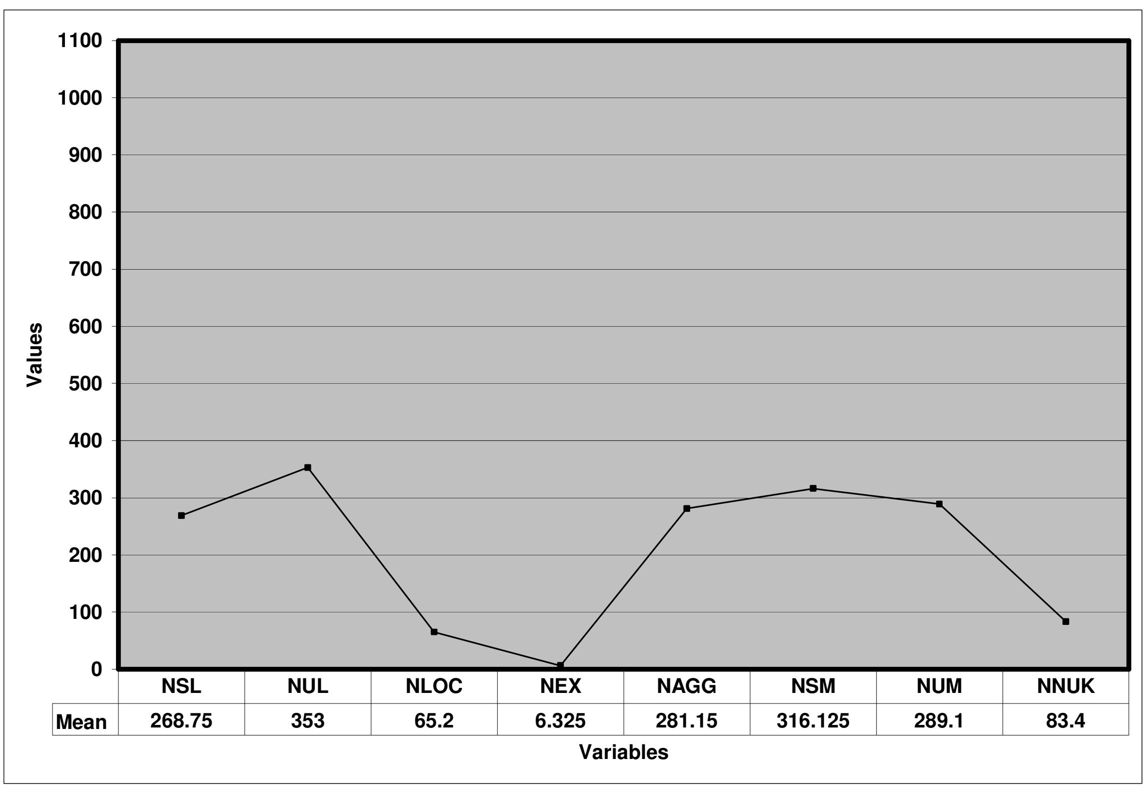


Figure 5.5: Mean of the sample (n= 40).

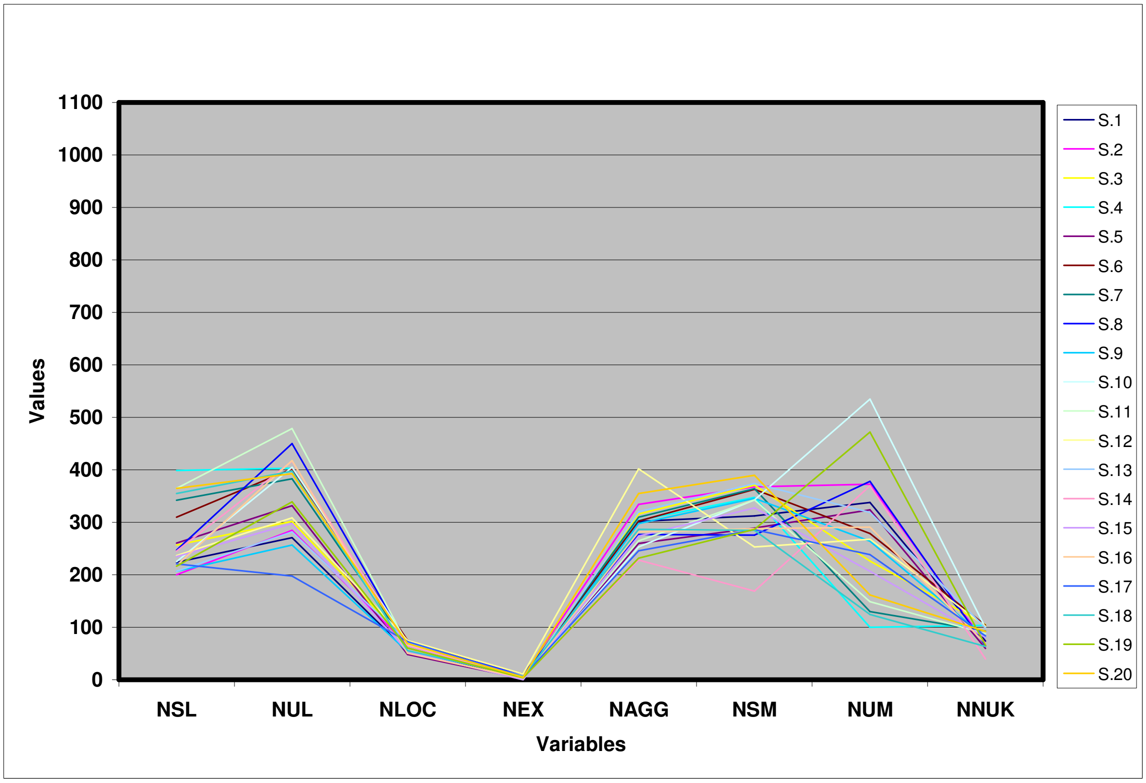


Figure 5.6: Results of group-A (n= 20).

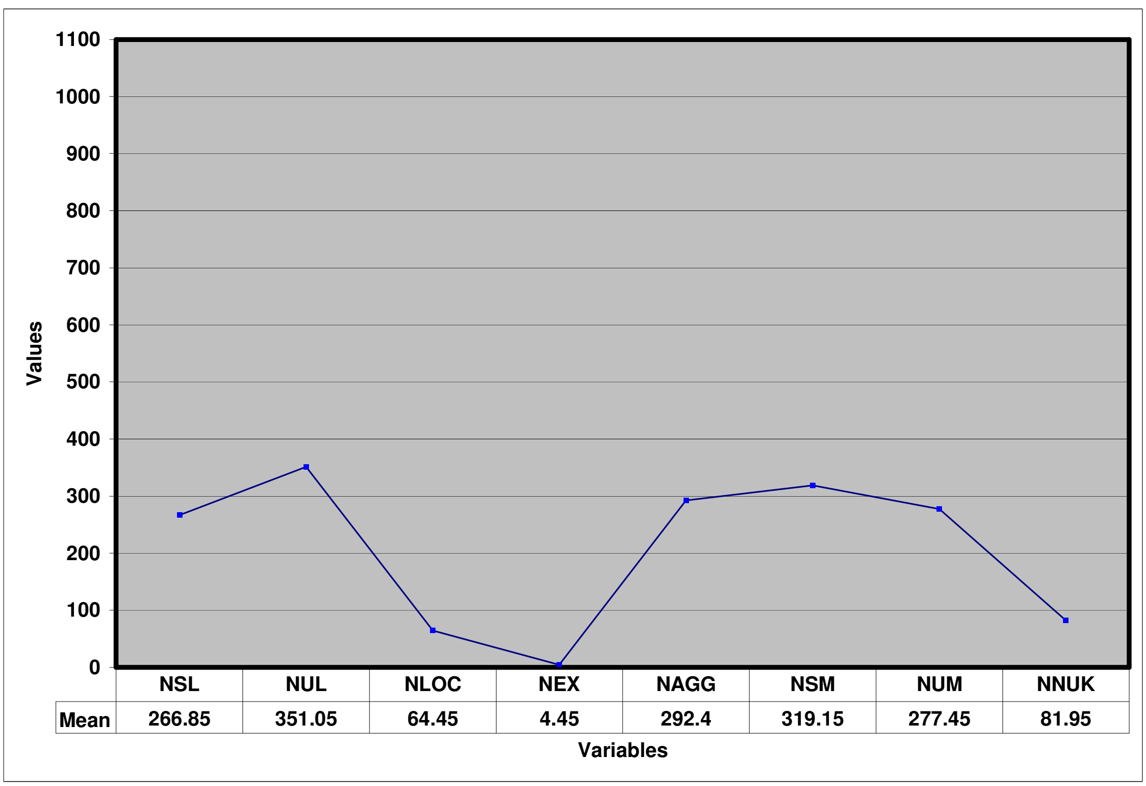


Figure 5.7: Mean of group-A (n= 20).

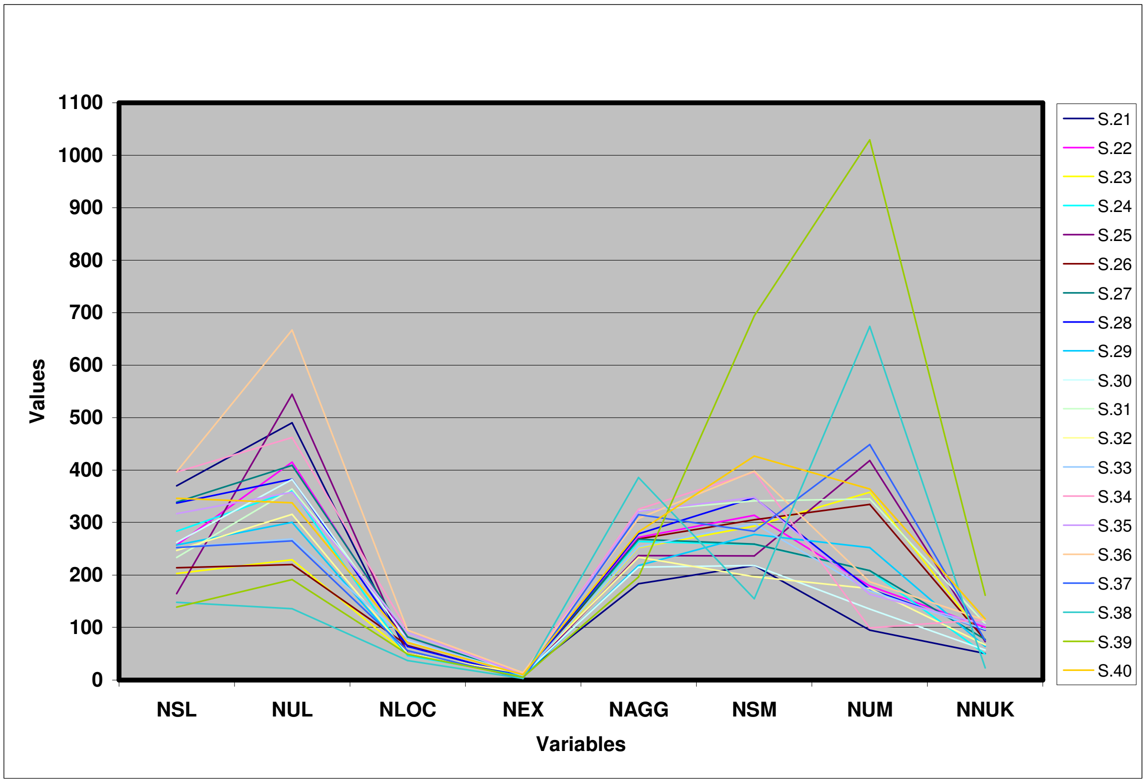
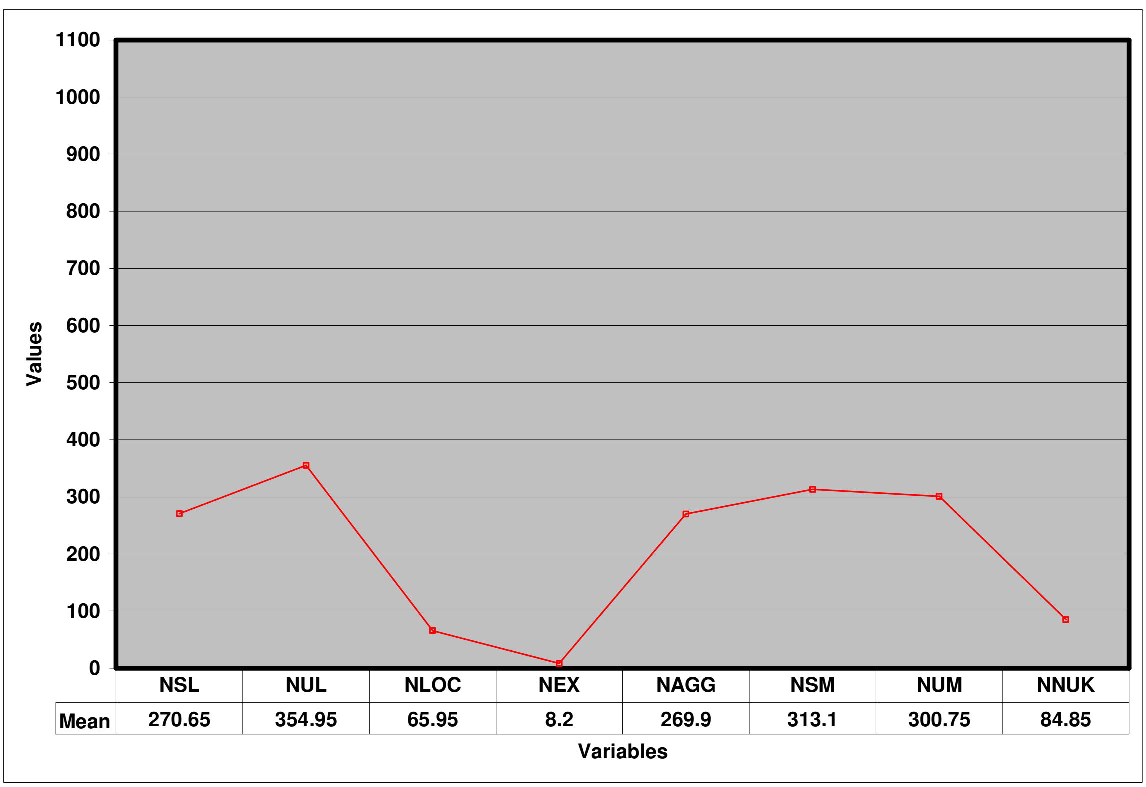


Figure 5.8: Results of group-B (n=20).



	NSL	NUL	NLOC	NEX	NAGG	NSM	NUM	NNUK
Mean	270.65	354.95	65.95	8.2	269.9	313.1	300.75	84.85

Figure 5.9: Mean of group-B (n= 20).

5.2.2 Discussion

The results of the experiment show that for both two groups, there are no differences between their results on the eight dependent variables as it was shown in table 5.3 (results of group-A) and table 5.4 (results of group-B) and figure 5.3 (results of the sample, group-A and group-B). "Group-B" had relative number of breakdowns more than "group-A". This was expected, because "group-B" had played non-renewable resources version and "group-A" had played island-game version that its resources could be renewable.

The results of the experiment are consistent with our expectation and are confirmed by our hypothesis that participants had different motivations (e.g. uncertainty ad incompetence motives), action plans, resolution levels, selection thresholds during playing the island game.

Hence, different type of strategies had been formulated and used by the participants. These results support Dörner's argument (2003, p.78) that the island game requires a lot of different cognitive activities, namely goal-learning, learning action sequences, remembering, background-control, task-witching, planning, extrapolation to foresee the future and coping with time restrictions.

Taken together, these results indicate that further qualitative investigations are needed to figure out different subjects' strategies and to classify these strategies.

In next sections, we will introduce our description of these strategies in perspective of PSI-theory. In the next section, we are going to discuss the method that was used towards analyzing action regulation of different strategies and single cases of personality.

5.3 Method and Description of Major Terms

5.3.1 Introduction:

This section deals with the qualitative method that had used towards analyzing action regulation of different strategies and single cases of personality. That method had been used by Dörner and Schaub (1994) when they analyzed human action regulation during controlling uncertain complex problem. Moreover, it had been also used by Strohschneider and Güss (1998) when they investigated planning and problem solving (differences between Brazilian and German students). This method helped us to recognize planning, decision making, information processing and mistakes that the participants had used during playing the island-game. Of course, that consequently helped us to set up PSI-parameters to simulate such action regulation strategies of participants and the two single cases.

5.3.2 The Method:

Dörner and Schaub (1994) mean by action regulation the interaction of goal elaboration, forecasting activities, hypothesis formation, planning, decision making and self reflection. Figure 5.10 shows phases of action regulation, as it has been described by Dörner and Schaub (ibid). In the following, briefly description of the basic concepts of action regulation will be demonstrated using island-game as an example of the description.

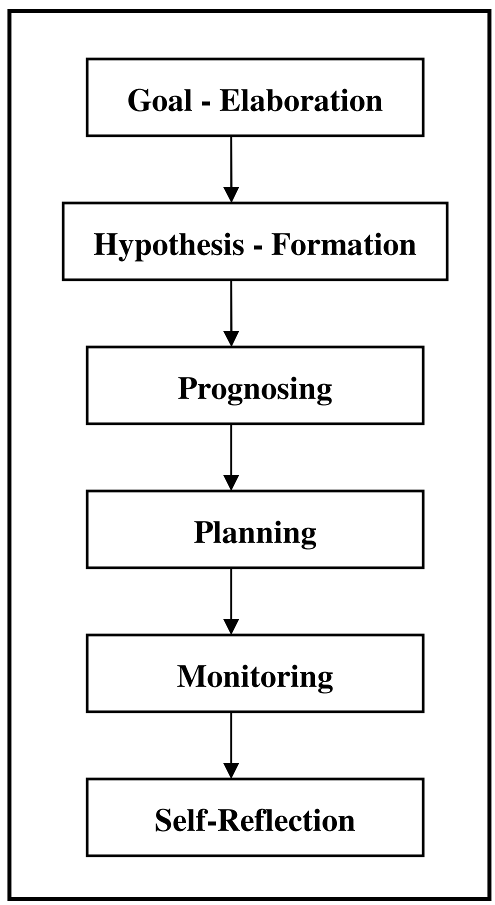


Figure 5.10:
Phases of action regulation.
Source: (Dörner & Schaub, 1994).

Goal-Elaboration:

In island-game, the goals were both ill-defined (open) and well defined. An open goal was, for instance, the task of taking care of the robot "James"; whereas the task of collecting nucleotides as much as possible was well defined. Dörner and Schaub (ibid) proposed that it was rather common that subjects in situations with ill-defined goals did not at all spend much time and effort in the elaboration of goals."

Hypothesis–Formation:

In such task, like island- game it is necessary to develop hypotheses to understand the functions of both operators and objects, and to explore the structure of the island. Dörner and Schaub (ibid) found that most mistakes in information collection are "channeling errors", which result from a preformed image of the reality. Dörner and Schaub (ibid) added that the subject was not prepared to look at the whole range of information, but only to a narrow part which he, according to his image of the system, considered to be important.

Prognosing:

In general, prognosis is a prediction of the probable course of events or outcomes of actions. Dörner and Schaub (ibid) argue that it is very difficult for us to build a good image of what is going on in time. We have difficulties in understanding the characteristics of developments simply because we forget so much. Therefore, the images we form about developments are often too simple. Moreover, prognoses will be especially difficult, when subjects fail to understand long-term developments and the developments are not monotonic, but exhibit more or less sudden changes in direction of development.

Planning:

Dörner and Schaub (ibid) elucidated that planning means to create new courses of action by a combination of pieces which the planner finds in his memory "model of the world". With complex systems, the main mistake of planning seems to be to disregard side effects and long-term effects, which nearly every action will have. It is not uncommon to find that the process of planning is guided not by the goal, which should be achieved, but by the salience of the effects of one's actions.

In addition, Strohschneider & Güss, (1998) clarified that planning is based on the knowledge of the given situation and uses knowledge about possible measures, their conditions for implementation, their main- and side-effects and their probability for success in order to find a sequence of steps that has a satisfying chance to reach the intended goal(s).

Strohschneider and Güss, (ibid) described plans, in perspective of the purpose of their study, on different dimensions as the following:

- **Depth, time perspective:** Plans can have a different time perspective. They can be "short" in the sense that their range encompasses only the immediate future. Plans with a "deep" time perspective consist of a long sequence of actions that reaches far into the future.
- **Concreteness:** Plans can be very abstract; general outlines of the intended course of action (one might call them strategies), or they can be very elaborated; detailed prescriptions for a specific sequence of actions.
- **Coherence, or structuredness:** They refer to the fact that actions may be related to each other or that the plan basically consists of a cluster of unrelated possibilities.
- **Width, or number of "branches":** Independently of their time perspective, plans can be narrow and consist of just one course of action or they can be wide and take different possibilities and events that might happen into account.
- **Flexibility:** Rigid planning does not allow for any detours of the planned course of action, although detours might be sometimes necessary.

Monitoring:

Dörner and Schaub (1994) argue that decisions in a complex situation often have long "dead-times". Successes or failures are not immediately visible, but will show up only after days, months or even years. Feedback-delay makes the control of the appropriateness of ones actions difficult. The non-cohesion of decision and effect will often lead to an abandonment of monitoring the effects of ones actions.

Self-Reflection:

Dörner and Schaub (1994) argue that if one induces self-reflection, one can improve the capabilities of problem-solving considerably. The abandonment of phases of self-reflection is often caused by the tendency to avoid doubts about the appropriateness of one's thinking abilities. Self-criticism implies the recognition of the mistakes that one has made, and this may mean a loss of the feeling of competence. A high feeling of competence, however, is just what seems to be extremely needed in complex problem-situations. The abandonment of self-reflections means that one will be caught in a vicious circle of incompetence. Error-prone thinking tendencies are not detected, therefore, a lot of errors will result and actions will not have the desired effects. The ineffectiveness of one's actions, however, endangers the feeling of competence and therefore one tries to avoid the confrontation with the errors, which in turn blocks reflections about the reasons of the mistakes (ibid).

5.3.3 Strategy, and tactics:

Every participant had his own strategy and tactics to fulfill the game criterions. A subject's strategy is the set of decisions-based on his motives' structure-made to achieve desired goals. It involves how the participant will achieve goals, and what is the important and what is not. Because strategy means that one has determined, in advance, an ultimate goal he would like to achieve. Therefore, strategy is making a choice amongst multiple choices. In strategy, comprehensive planning* and a conducted long-term plan of action are considered (sometimes a participant does not care about long-term plan rather short term plan). Here, planning determines how the participant will learn about the structure of the island-environment and how he shall discover it. In general; plan in strategy is much more cohesive than a hastily constructed one. Strategy is immutable, because it is considered as a big picture look at a problem and it gives us the course of action we take as we attempt to achieve our goals.

* For further details about strategy and planning see (Dörner, 1989, p.95-97).

Tactics are the set of actions or activities taken to reach specific goal or goals towards fulfilling a strategy. One can describe a tactic as a device for accomplishing an end; a method, or a set of requirements for a plan to take effect. Hence, tactics are what we do to carry out strategy (in other words, the actual ways in which the strategies are executed).

Also, tactics are seen as an aspect of strategy and not an end in themselves. Tactics vary with circumstances. Therefore, tactics present a small picture perspective. Strategy is what one wants to do, while tactics are the means to reach that aim. Briefly, a strategy can be a sum up of a number of tactics (see figure 5.11).

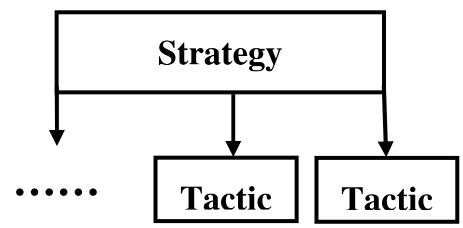


Figure 5.11: Strategy and tactics.

Dörner (2001) and Starker had found the following participants' strategies that were used after playing an early version of island-game (version II*).

1. **Survival-strategy:** Try to find as much water, hazel-nuts and sunflower seeds as you can.
2. **Basis-Camp-strategy:** Find a place where a lot of water and fuel exist. Use this place as a basis camp for expeditions to collect nucleotides and turn back to this place when the vehicle begins to run out of water or fuel.
3. **Nucleotides-first-strategy:** Don't care about the vehicle. You'll get a new one after each breakdown.
4. **Action-strategy:** Try to be as active as possible. Change whatever can be changed.
5. **Carpe-diem-Strategy**: Don't waste your time with long-term planning and strategy formation! Look for the opportunities of the moment.

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* Version-II Is a small version of the island game that contains fewer objects and locomotion than version III that had been used in our experiment, but has the same task and motives that are in version III).

5.3.4 Discussion

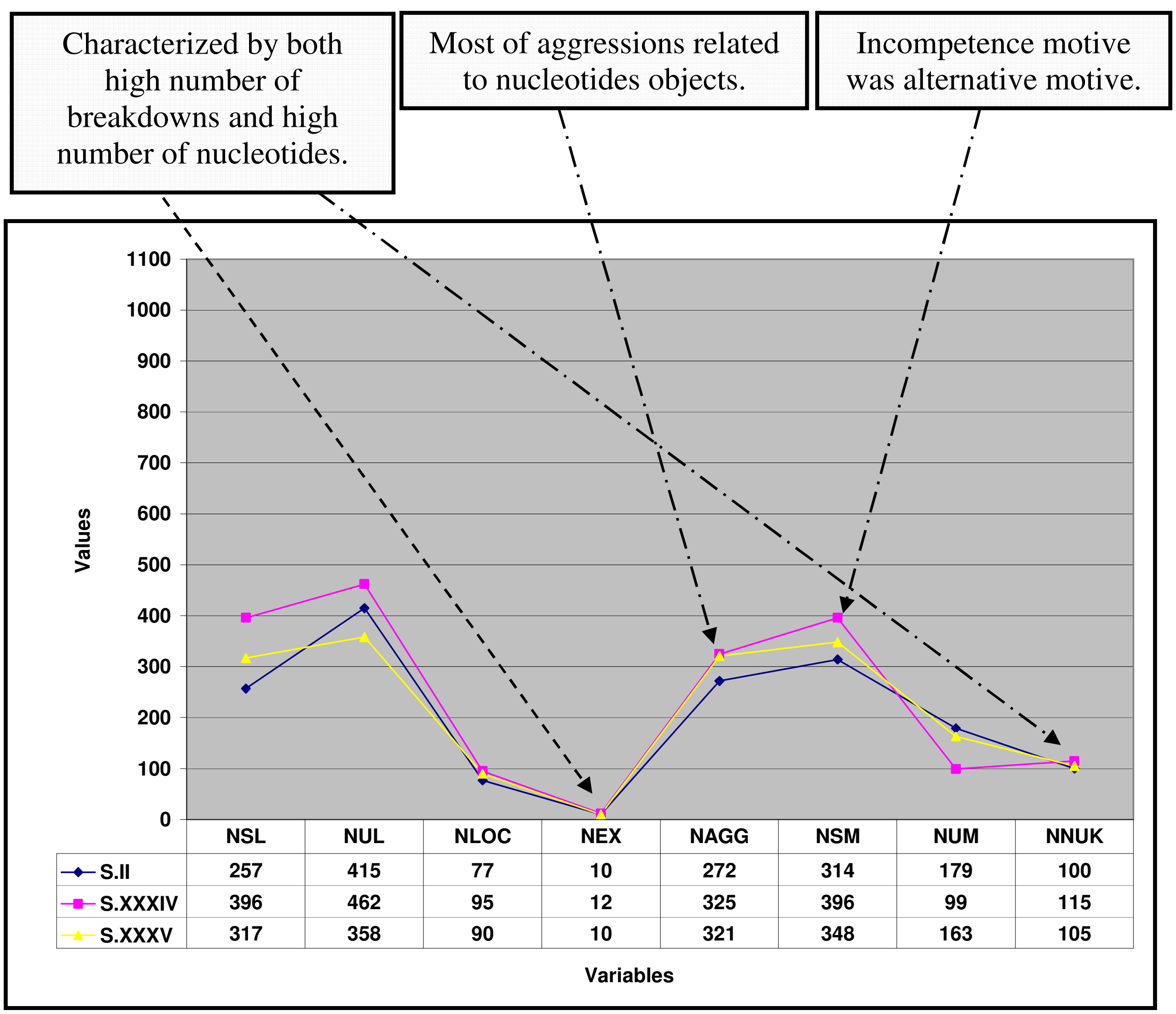
In the current research, we also observed the strategies that Dörner and Starker had investigated in island-game version II. Moreover, we also discovered two new strategies (stereotype-strategy and balance between motives strategy). In the current work, we simulated two strategies that had been considered by Dörner and Starker (**survival-strategy and nucleotides-first-strategy**), because they had been also used by participants when they had played island-game version III. Moreover, we simulated the two new strategies that we had found by the participants, when they had played island-game version III too. These two new strategies are **(stereotype-strategy and balance between motives strategy).** In the following, we are going to explain these strategies in perspective of PSI-theory. Firstly, we will discuss nucleotides-first-strategy. We will explain action regulation of subjects those who used this strategy. Secondly, uncertainty and incompetence motives, resolution level, selection threshold and action process of subjects those who used balance between motives-strategy will also be discussed. By simulating these two strategies; nucleotides-first-strategy and balance between motives-strategy, in perspective of PSI-theory, we can assume that PSI-agent is able to simulate different human strategies in a complex and dynamic task. Moreover, we viewed the PSI-agent as potentially having the ability to simulate all strategies that humans can do in complex tasks. Therefore, we assumed that it makes sense, when PSI simulates single cases too. Taking this view, we have analyzed and then simulated (participant-XXVIII)'s strategy, as an example of balance between motives- strategy). We also simulated (participant-XXXVIII)'s strategy as an example of stereotype-strategy. While in chapter six we will show the simulation process, in the following, we will demonstrate the analyzation process of actions for these four different strategies.

5.4 The Nucleotides-First-Strategy

5.4.1 Introduction:

In general, participants who used the nucleotides-first-strategy during playing the island-game had considered nucleotides as a main motive and they had ignored the existential needs (hunger–thirst–damage avoidance) and affiliation motive too.

In the first session of playing island game, they had high level of uncertainty and the other three sessions their actions were characterized by high level to collect nucleotides. Figure 5.12 shows action profiles of three participants who used the nucleotides-first-strategy. We can notice that these profiles are characterized by high number of breakdowns (because the participants ignored the existential needs) and high number of nucleotides (because searching nucleotides was their main motive). And because searching nucleotides was their main motive, Most of



	NSL	NUL	NLOC	NEX	NAGG	NSM	NUM	NNUK
S.II	257	415	77	10	272	314	179	100
S.XXXIV	396	462	95	12	325	396	99	115
S.XXXV	317	358	90	10	321	348	163	105

Figure 5.12: The nucleotides-first strategy–action profiles.

aggressions related to nucleotides' objects.

We noticed also that participants, who used nucleotides-first strategy, did not consider "Teddy"; the affiliation's goal in the game, one of their goals, because they were always in a hurry to collect many nucleotides as they could. And they considered satisfying affiliation's motive could slow down and reduce the number of nucleotides (their main goals). Therefore, one can estimate that affiliation's motive was reduced or played no role with these participants during collecting nucleotides. That means affiliation motive should have a very small weight value, when we simulate participants who used nucleotides-first strategy. Basic characteristics (e.g., motives, resolution level and tactics) of action profile of the participants, who used nucleotides-first strategy, will be illustrated as follow.

5.4.2 Uncertainty motive:

Island game was not a simple mission because there are many difficulties and problems that faced the players or the participants during playing the island game, and they had to solve these problems. For example, the participants did not know the geographical structure of the island; therefore, they had to explore the geographical form of the island and learn where and how one could move between the different places (see: Dörner, 2001; Dörner; 2003; Dörner, & Schaub, 1998). Moreover, in order to satisfy uncertainty motive, a participant had to find out solutions for the following questions or problems:

- Which objects can be considered as goals for hunger and thirst motives?
- Which operators can be used to manipulate these objects?
- Where can one find these objects?
- How can one avoid damage?
- How can one repair damage?
- Are there particular objects that could help to fix the robot?
- Where can one find these objects?

Participants, who used nucleotides-first strategy, had a high level of uncertainty motive in the first session. And because they wanted to reduce their uncertainty, they had manipulated objects and operators to discover and detect their meaning and their purposes. Therefore, they continuously tried to find the meaning underlying things. Every encounter and every piece of knowledge gained had been applied. Then, this experience was evaluated to see if it had any consequence to help them to get their goals. Participants, who used nucleotides-first strategy, had used the following tactics to satisfy uncertainty:

A. Searching general certainty about all objects, operators, and locomotions. Participants had explored all objects in a locomotion by using most of the operators. Moreover, participants tried to do that very quickly as possible, thus they can explore different locomotions. Such participants were characterized by acting very fast and were motived to acquire certainty about surroundings. Hence, satisfying uncertainty motive should have a high priority in their parameter list accompanied by high selection threshold. Consequently, their results were characterized by high number of aggressions, high number of successful manipulations, high number of successful locomotions and high number of locomotions. Yet, because they had high level of uncertainty motive, they sometimes collected few number of "nucleotides" in the first session because they had spent much time in exploration process and consequently, they had high number of breakdowns (see figure 5. 13).

B. Searching certainty about most objects, operators, and locomotions. Here, the participant, who used nucleotides-first strategy, explored most objects in locomotion, instead of exploring all objects. In addition, the same tactic occurred when the participant had explored operators too. To simulate such tactic, one can assume that satisfying uncertainty motive should have a high priority in their parameter list, their selection thresholds should also have a moderate level that allows other motives to be active and thus target for next action and that just in the first session. Consequently, results of the participants, who used nucleotides-first strategy and used also this tactic, were characterized by high number of aggressions, high number of successful manipulations, high number of successful locomotions and high number of locomotions. Of course, these dependent variables were fewer in their values than the previous tactic. As well, because of their moderate level of selection threshold, they collected a high number of "nucleotides" and had a few number of breakdowns compared to previous tactic (see also figure 5.13).

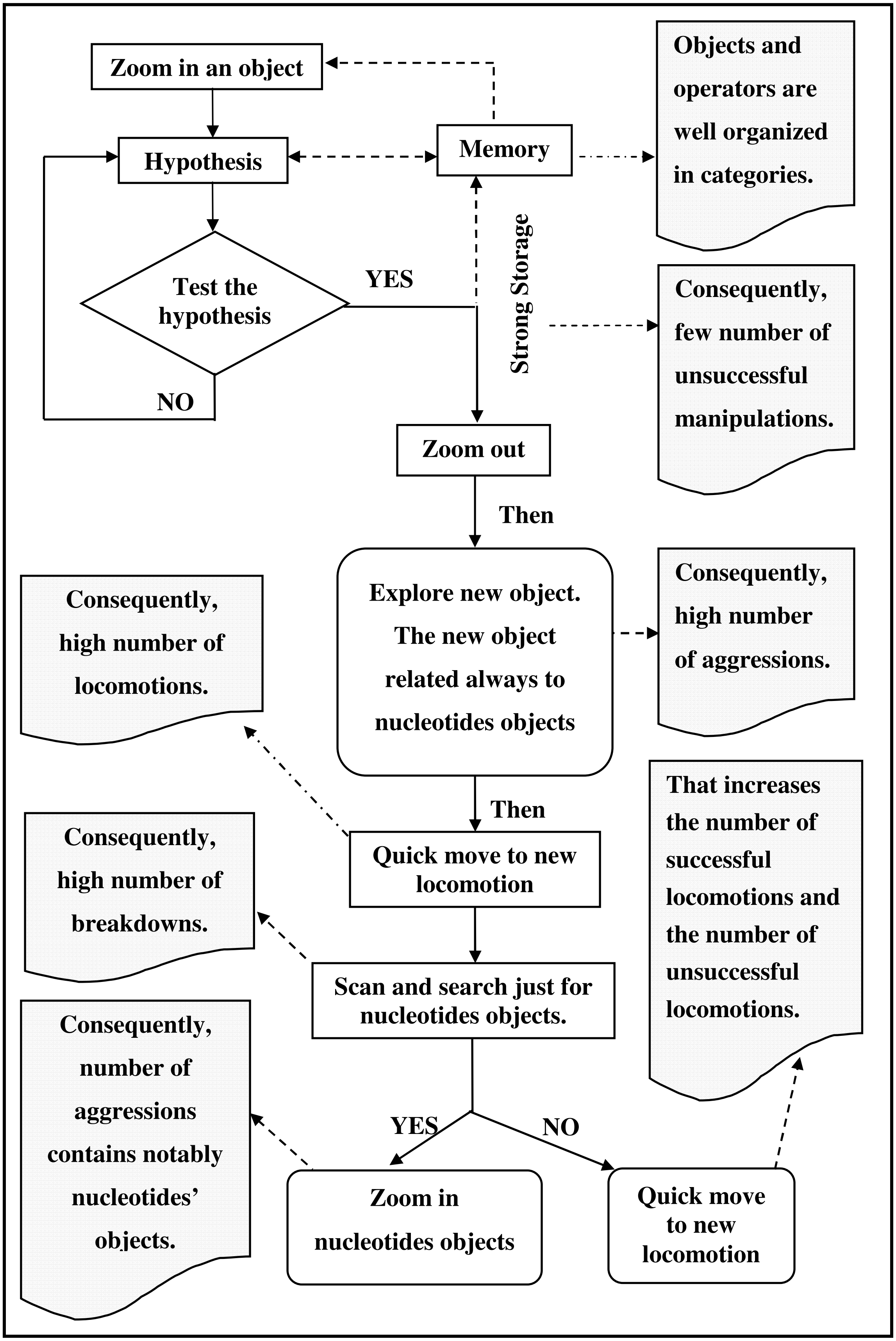


Figure 5.13: The nucleotides-first-strategy– action process.

C. Formulating hypotheses about objects and operators before acting.

In this tactic, participants built hypotheses about objects and their relations to motives. For example, "water" as a goal could satisfy thirst (right hypothesis). An example of wrong hypothesis is that "a tree" could satisfy hunger. For this reason, they explored just objects that match their hypotheses. Moreover, they used the same tactic with operators and their relations to objects. For example, the sucker operator could suck water. As a result, they chose few number of objects and test them by few numbers of operators and consequently, they had got few number of aggressions and few number of successful manipulations. And before they chose an operator from operators list to make it active for action, they had spent relative much time to formulate a right hypothesis (see figure 5.15). This tactic was considered as a great source of competence, because competence increased very high after a hypothesis was successfully proved. However, it was also considered as a source of incompetence, because competence decreased after a hypothesis was failed as it is shown in figures 5.14*. Moreover, classification process was considered an essential step towards exploring objects and operators. At this point, a subject attempted to classify the surroundings into two main and primary categories (known and unknown). Figure 5.13 shows effects of classification process of objects, in perspective of known-unknown criterion, on

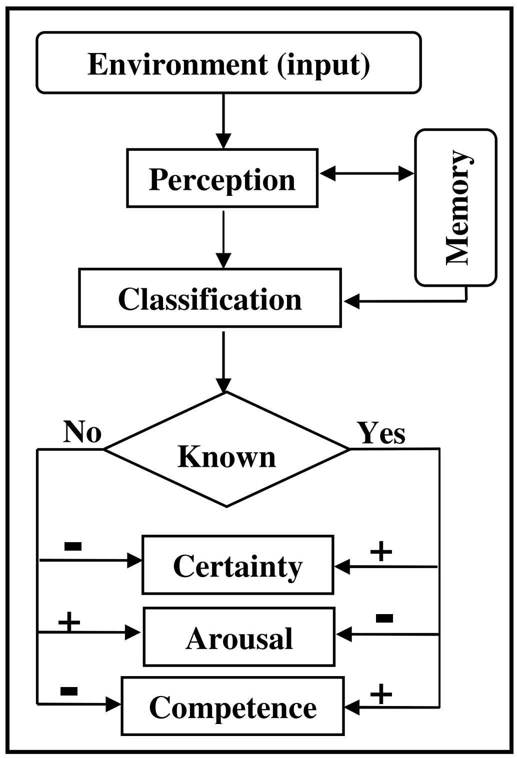


Figure 5.14:
Effects of the classification process.

* It apparently seems that the results of figures 5.14 and 5.15 were early introduced in PSI-theory, however the current results support what was before found and vice versa.

arousal and both certainty and competence. For example, while a known object increased the participant's certainty and competence, it decreased at the same time the participant's arousal.

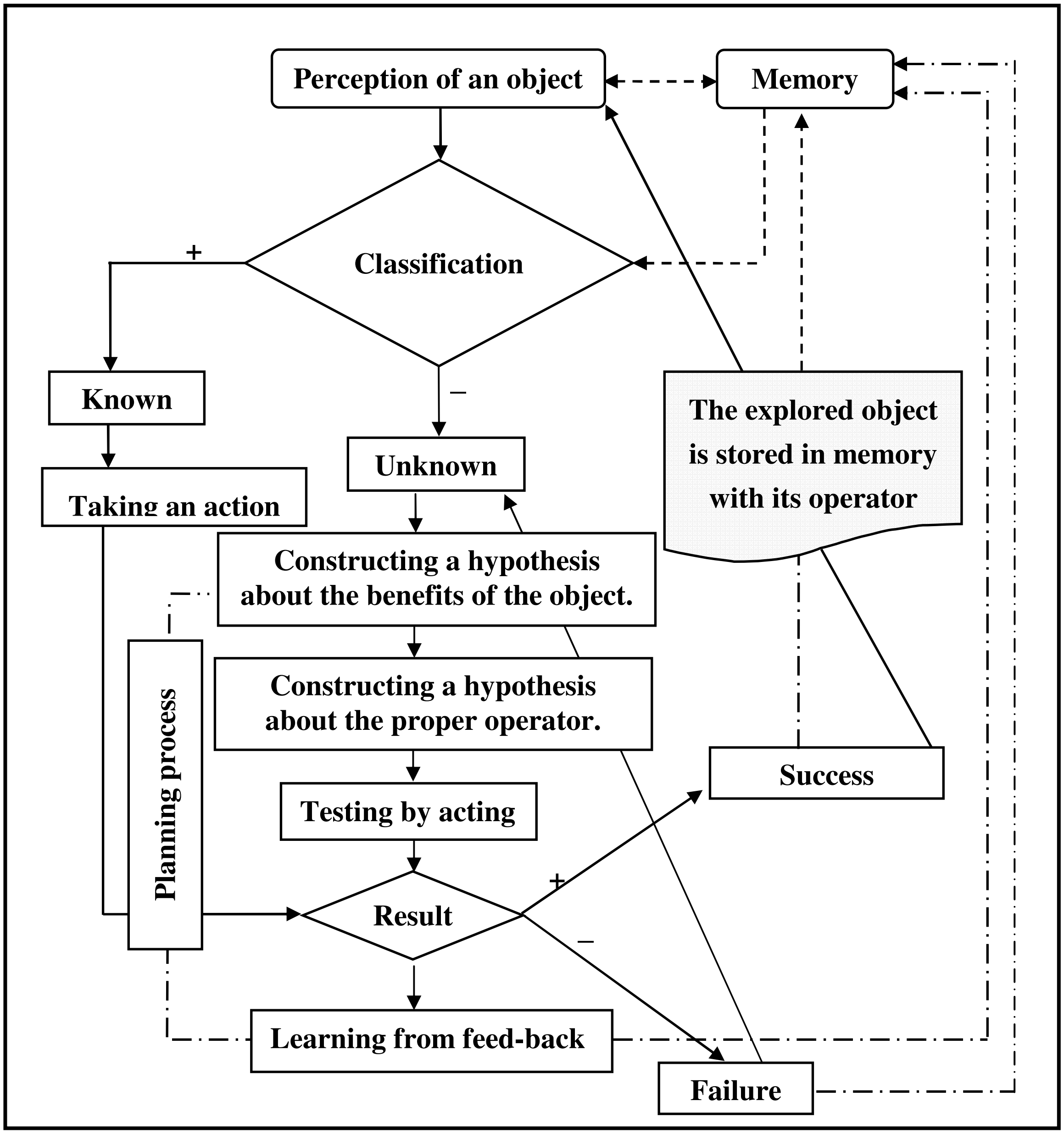


Figure 5.15: Classification process and formulating hypotheses.

Participants, who used nucleotides-first strategy and used also this tactic, preferred planning to simple acting without planning. When this tactic had success, a participant began to act steadily and his results were also characterized by high number of "nucleotides". But when this tactic had failure, a participant's competence had decreased and his action began to be unconfident. However, most those who used nucleotides-first strategy had a high level of persistence; therefore, they had reformulated new hypothesis (try new operator) till they found the effective one (see figure 5.15). Planning steps as it was shown in figure 5.15 will be briefly explained as follow:

1- Constructing a hypothesis about usages and benefits of the object.

Before a participant, who used nucleotides-first strategy, began to act, he attempted to construct a hypothesis about the benefits of the objects. This prediction phase was considered a result process from the interaction between the participant's memory, motives, and the current object. This interaction process apparently coasted time. However, the benefit of constructing a hypothesis about the object was especially important because this process reduced much time in the next action steps and consequently, it reduced number of unsuccessful manipulations during playing sessions.

2- Constructing a hypothesis about the proper operator.

After zooming in an object, there were different operators that a participant could select one of them to handle the object. Here, the participant attempted to construct a hypothesis about the proper operator that could be proper to handle with the current object. Of course, participants differed from each other in respect of these two phases. It was recognized that most of them used these two phases, while random choices, during the exploration process, had been made by the others.

3- Testing by acting.

It is rational that when one attempts to prove a hypothesis, he takes an action. However, it was observed that some of the participants just pointed to an operator without taking action (e.g. click on the operator to activate it for manipulation). In this case, the operator was not applied and the hypothesis was not proved.

4- Learning from feed-back.

After activating an operator, one can observe if it is effective or not. Inadvertently, some participants did not observe the effect of the operators, while others did. The reason for that could be due to the participant's resolution level. When one has a high resolution level, he could see and observe the effect, while low resolution level interrupts one's perception. Learning from feedback about results is important because one should have relevant feedback and consequences about his performance. Participants, who used nucleotides-first strategy, used the feedback information about the result of a process or activity to guide them to next steps. They also learned by trial and error. They stored automatically information according to both outcomes (success and failure) for future retrieval, so they had saved time by avoiding mistakes (e.g., using useless operators). As well, they were likely to retrieve the steps that had been previously experienced, and then they applied these steps. Also, because they had stored experienced information from feed-back, they could skip steps towards solutions more quickly than participants who used stereotype-strategy. Those who used stereotype-strategy did not use the feed-back efficiently, so they repeatedly made the same mistakes.

5- Re-plan.

When the operator was failed, the participant, who used nucleotides-first strategy, replaned and tried again by using another operator, till he had found the right operator and conditionally stored both object and its operator in memory for future retrieval. Here, the participant put a lot of energy to identify the best tactic to reach his goals.

D. Exploring systematically an object by all operators.

Sometimes, a participant; who used nucleotides-first strategy, began to explore an object by all operators and without formulating hypothesis. He followed systematic order as shown in figure 5.16. The systematic order if this tactic was as follow.

1. A participant zoomed in an object, and then he explored it by using the operator (A). When the operator (A) failed to make change or had no effect then;
2. The participant activated the next operator -"the operator (B)" -, and when it failed to make change or had no effect then;
3. The participant activated the next operator- "the operator (C)" -, and when it

had effect and the object was changed then;

4. The participant explored the object again, or zoomed out and then;
5. The participant explored systematically new object.

In first session, action profiles of those who used nucleotides-first strategy were characterized by high number of unsuccessful manipulations. However, in the next sessions, the action profiles were characterized by high number of successful manipulations.

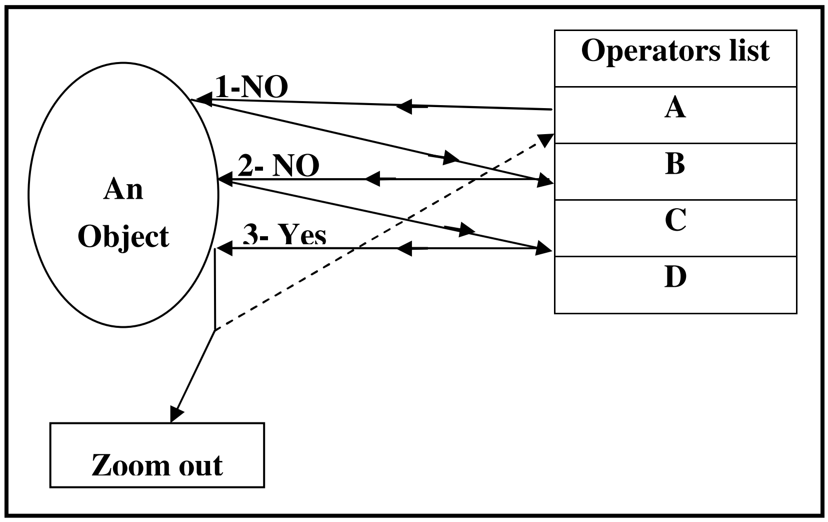


Figure 5.16: Exploring an object systematically.

E. Exploring geographical structure of the island by choosing a direction from directions' list similar to the clockwise direction.

In order to move to new location or to explore geographical structure of the island, participants used clockwise direction tactic as it is shown in figure 5.17. The systematic order of this tactic was as follow:

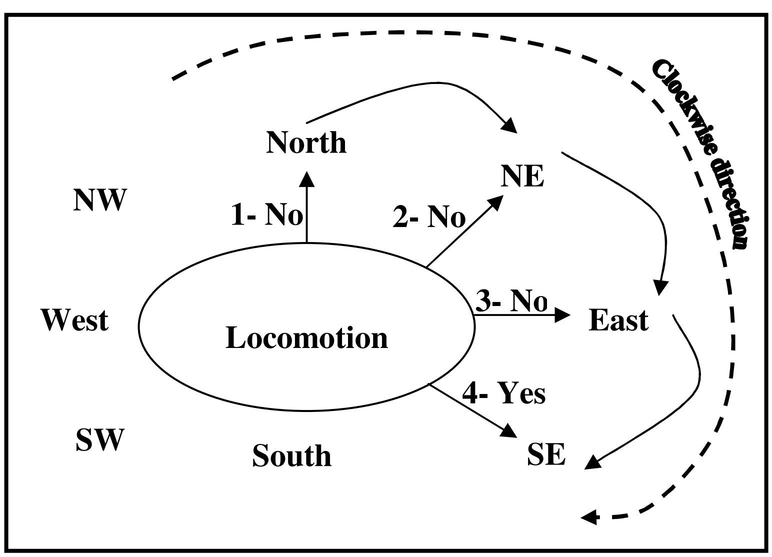


Figure 5.17: Clockwise direction tactic.

1. A participant clicked "North-direction" to move to new location. When "North-direction" failed or was blocked then;
2. The participant clicked "NE-direction" - and when it failed or was blocked the participant clicked "East". When "East-direction" was blocked then;
3. The participant clicked "SE-direction" and came in to a new location. And to move to new location, a participant clicked again "North-direction"……..etc.

5.4.3 Incompetence motive:

Participants, who used nucleotides-first strategy, acted confidentially and assuredly and they searched for success. Yet, success for them meant collecting many nucleotides as possible. In other words, they focused on the way that made their competence high. They did not want to feel incompetent or inadequate. Therefore, they tried to act in such way that made them competent and successful. Moreover, they minimized the effect of failures or such behaviours that made them feel incompetent. Hence, the increase of competence was higher than the decrease of competence. When their goals were being threatened and at risk of becoming endangered, they can become aggressive (towards environment; i.e., beating affiliation goal or towards the robot; i.e., ignoring the robot's needs) and inclined to behave in a hostile fashion to protect their goals.

In addition, because those who used nucleotides-first strategy seemed that as they did not accept mistakes, they tried to complete tasks to the final detail without mistakes (e.g., they explored objects by all or most operators till they were sure that the objects were completely explored). They heavily had used their intuitions; therefore, they sometimes know things intuitively by getting feelings about them, and then they checked their intuitions by systematic verification. Because they had determined very high standards of action especially towards collecting nucleotides, they were usually hard pressed; did not give themselves enough breaks and seem unhappy. Moreover, they sometimes were not satisfied about their actions or results and that was because of their high level of aspiration. Moreover, they were very sensitive to conflict situations. For instance, when the robot would breakdown and at the same time, there was a chance to collect nucleotides. Therefore, situations, which were charged with conflict, may drive them into a state of anger or confusion, and that clearly appeared in their facial expressions (i.e., stressful emotion).

5.4.4 Resolution level:

Participants, who used nucleotides-first strategy, were sensitive to differences between objects, especially nucleotides objects. One can assume that they had a high resolution level and they worked enthusiastically to collect many nucleotides. Moreover, they did not focus on the other objects, except that served their main task (nucleotides). They stored nucleotides objects and their operators in memory. Hence, they could quickly elicit and determine the operator, when they found a nucleotides object. Therefore, their profile was characterized by few number of unsuccessful manipulations and high number of successful manipulations.

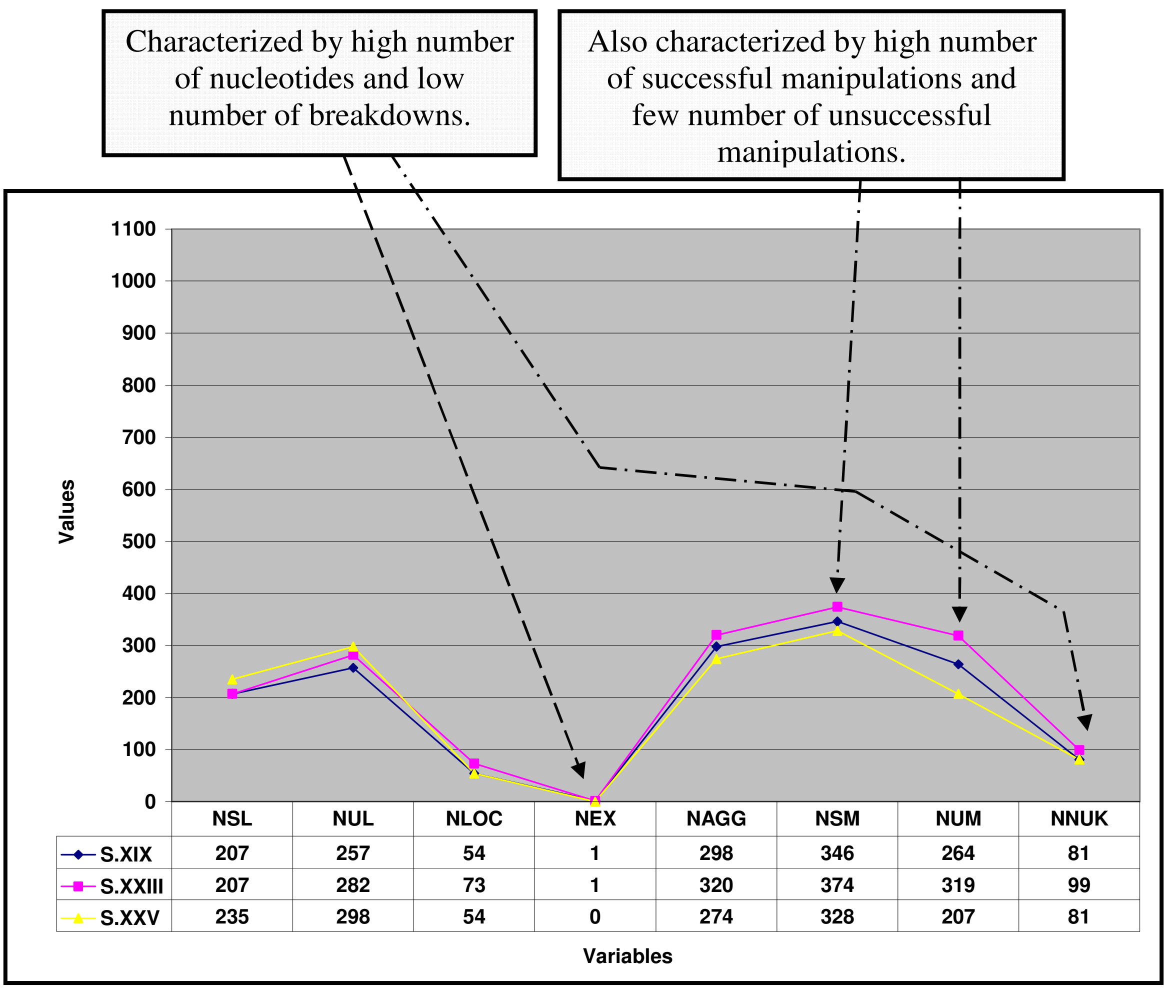
5.4.5 Selection threshold:

Participants, who used nucleotides-first strategy, had high selection thresholds towards collecting nucleotides and, at the same time, they did not make balance between motives. For example, when they were in a locomotion, they scanned and searched just for nucleotides objects. In conflict situations, whereas one of the robot' motives was high, they display little importance to the robot' motives. They simply try to achieve their main goal (nucleotides), regardless the consequences that the robot can suffer. For example, when the robot was in danger and it should have been repaired and, at the same time, there was a chance to collect nucleotides, they did not repair the robot rather than they had collected nucleotides. They would not reduce their high level of aspiration to save the robot; therefore, the robot had frequently breakdowns. For this reason, they had high number of breakdowns and, at the same time, they had high number of nucleotides (see figure 5.12).

5.5 The Balance-Between-Motives-Strategy

5.5.1 Introduction:

Some participants played the island game and they made balance between motives. In other words, some participants were capable of achieving both tasks (saving the robot from breakdowns and collecting nucleotides) by considering all goals of existential needs together with nucleotides. These participants had moderate (medium) level of selection threshold and high resolution level that was important to notice differences very rapidly and sensitively. Therefore, they were able to store and easily recognize more details about objects and locomotions. We called these participants "productive subjects", because they had competently and efficiently achieved the both tasks (save the robot from breakdowns and collect nucleotides) in respect of comparing their results to the results of the sample as it will be shown in chapter six. Figure 5.18 shows action profiles of three participants who used balance between motives-strategy.



	NSL	NUL	NLOC	NEX	NAGG	NSM	NUM	NNUK
S.XIX	207	257	54	1	298	346	264	81
S.XXIII	207	282	73	1	320	374	319	99
S.XXV	235	298	54	0	274	328	207	81

Figure 5.18: The balance-between-motives-strategy – action profiles.

5.5.2 Uncertainty motive:

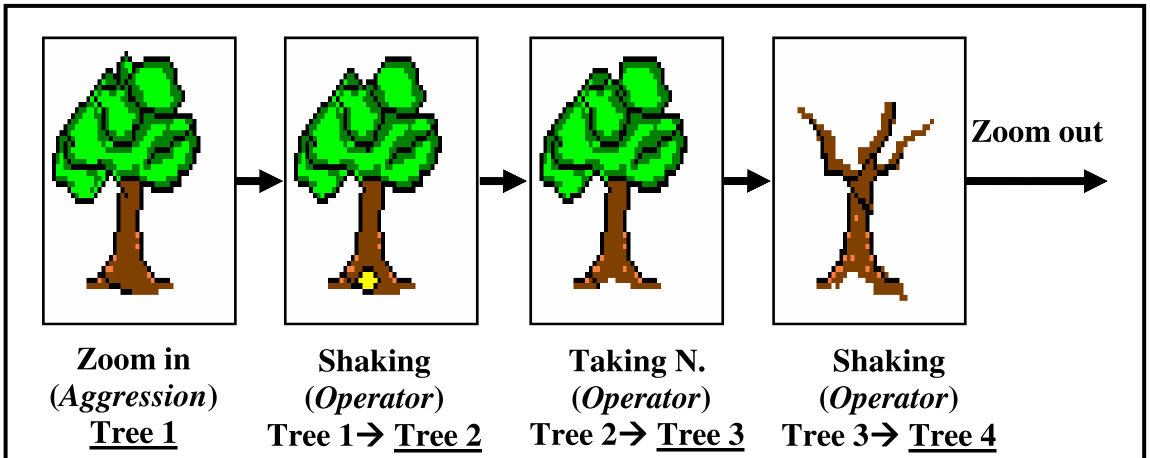
Participants, who used balance between motives strategy, had high level of uncertainty especially in the first session. They concentrated to satisfy uncertainty motive by focusing their actions to gather information about goals and their relation to motives. For example, after (30) minutes of playing the game, they had a large database about the tasks of the game. That included goals formulation, objects, operators and geographical structure of the island. They gathered and; then, coded information systematically in the memory. Therefore, they were quickly able to recall information from memory to solve new problems (situations). Tactics that had been mostly used to satisfy uncertainty motive by those who used balance between motives strategy will be briefly illustrated as follow:

A. Complete-incomplete action-tactic.

While most of participants, who used balance between motives strategy, used complete action tactic as shown in figure 5.19, some of them used incomplete action tactic as shown in figure 5.20. Complete-incomplete action tactics depended on a participant's uncertainty motive towards an object. To clarify, if the increase value of uncertainty motive was more than the decrease value, then a participant would use complete action tactic. While if the decrease value of uncertainty was more than the increase value, then a participant would use incomplete action tactic.

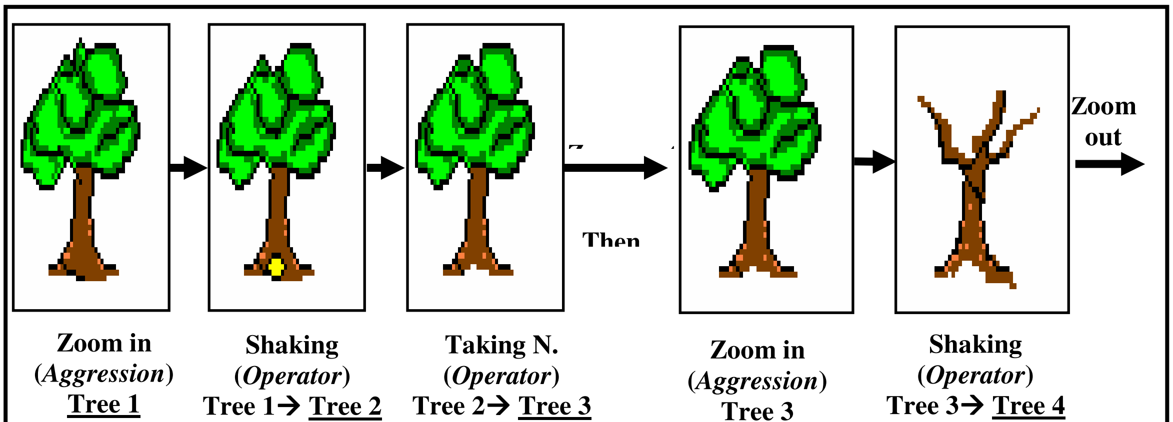
Moreover, participants, who used incomplete action tactic, assumed that every object had just one right operator and the other operators would not be useful, and the effect of an operator could change an object just for one time and no more. While participants, who used complete action tactic, assumed that every object could have one or more right and useful operators, thus an object could be changed more than one time by one or more operators.

In addition, what a (participant-A), who used complete action tactic, did in (90) minutes, a (participant-B), who used incomplete action tactic, did it in (120) minutes.



Sum	Aggressions	Operators
	1	3

Figure 5.19: Complete action tactic.



Sum	Aggressions	Operators	Plus approx. 15 seconds.
	2	3	

Figure 5.20: Incomplete action tactic.

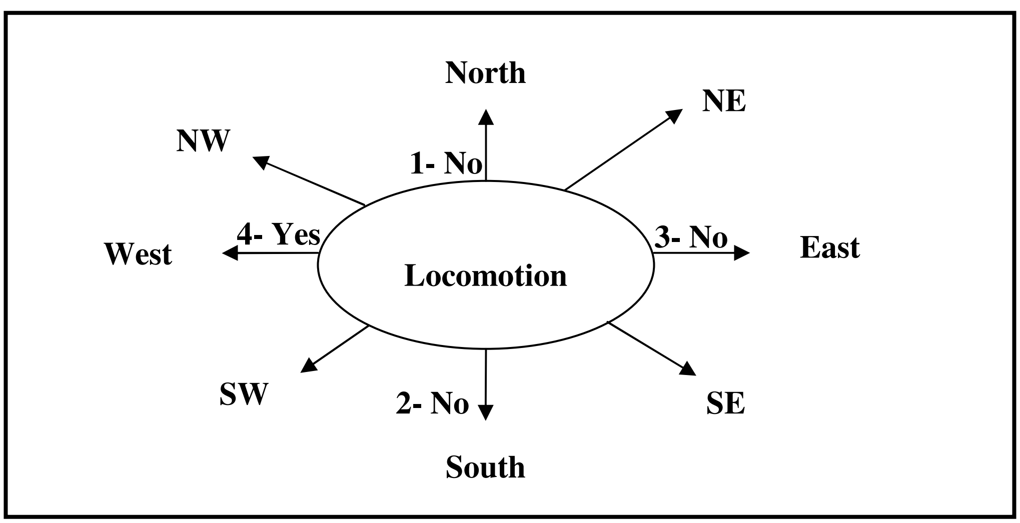


Figure 5.21: Bipolar-direction tactic.

To simulate these participants, we should do the following (see table 5.5):

1. The increase value of uncertainty motive of "participant-A", who used complete action tactic, should be higher than the increase value of uncertainty motive of "participant-B" who used incomplete action tactic.
2. The decrease value of uncertainty motive of "participant-A" should be lower than the decrease value of uncertainty motive of "participant -B".
3. In all circumstances, the resolution level of "participant -B" should be lower than "participant -A".

	The increase value of uncertainty	The decrease value of uncertainty
Participant-A (complete action tactic).	high	low
Participant-B (incomplete action tactic).	low	high

Table 5.5: Estimated parameters for complete and incomplete action tactics.

B. Exploring geographical structure of the island by using bipolar-direction-tactic.

In this tactic, a participant explored the island by bipolar-direction strategy; e.g. (North then South), (East then West), (NE then SW) or (NW then SE). For example, as it was shown in figure 5.21, a participant had clicked north in order to move to new locomotion, and when that failed; then, he clicked south.

C. Exploring an object in a locomotion, and then quickly move to new locomotion-tactic.

In this tactic, a participant had just explored an object in a locomotion, and then moved to new locomotion (see figure 5.22). This participant felt bored quickly and therefore, he had looked for new information. Therefore, the action profile of such participant was marked by high number of aggressions and high number of successful locomotions. To simulate such tactic, we should give the weight of uncertainty motive the highest value. Moreover, the increase value of uncertainty should also be high; therefore, the participant will look for information. Also, the decrease of uncertainty motive should be high; therefore, the participant (or the PSI-agent) will feel bored quickly.

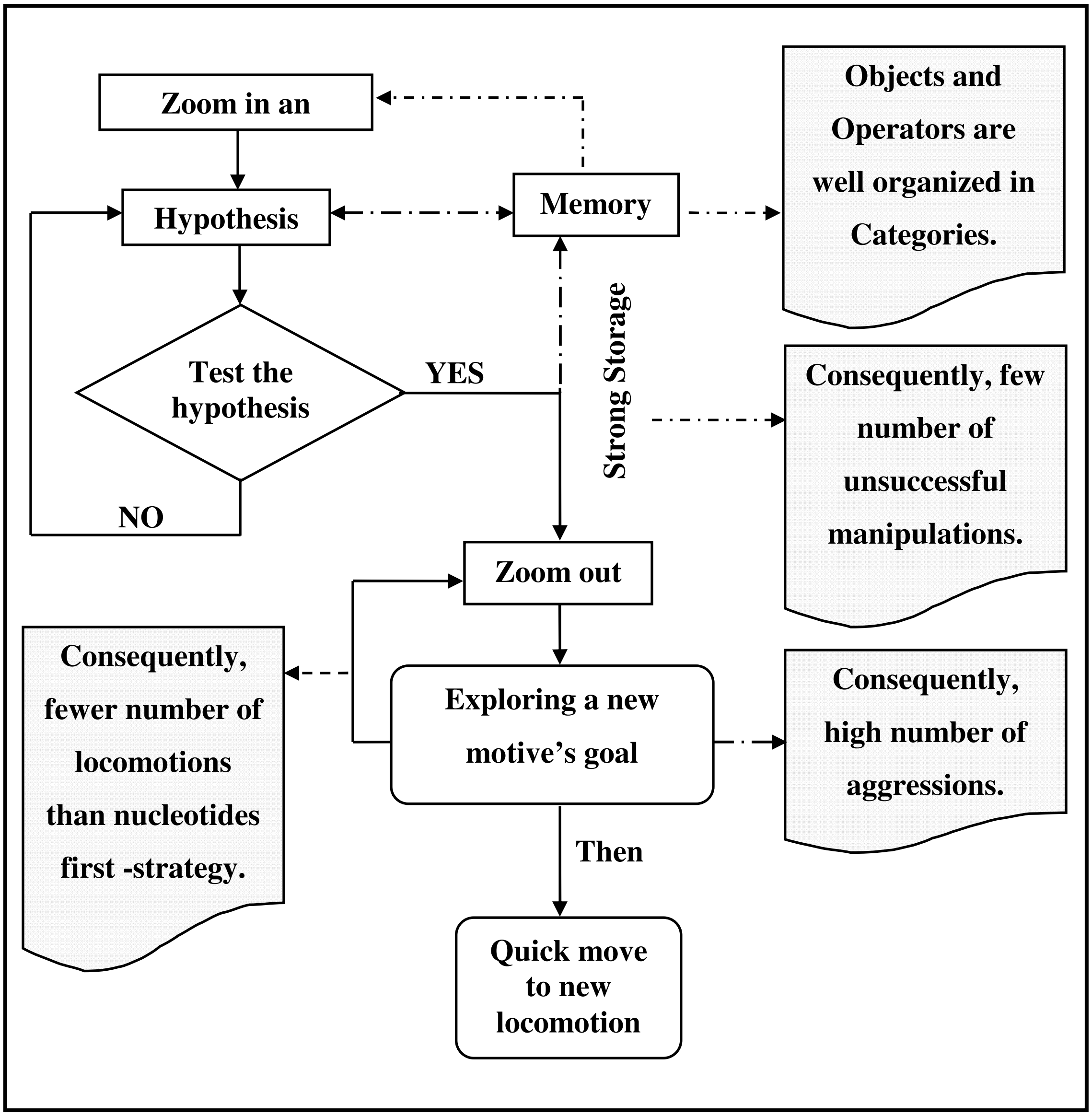


Figure 5.22: Action process of the balance-between-motives-strategy.

5.5.3 Incompetence motive:

Applying what a participant had learned about objects and operators to the new situation increases the participant competence. Participants, who used balance between motives strategy, used exploring-then–applying tactic (see figure 5.25) as a main source of competence. Applying known knowledge was one source to increase competence. They preferred to do things that they had known. They tried to maintain their competence always high by acting such action that led to success. Moreover, they began with things that the outcome prediction would surely be right and accordingly, their competence would be high. They explored new locomotions and objects to apply what they had learned and to prove their competence. Therefore, we can assume that a participant, who used balance between motives strategy, had a high value of incompetence motive. Therefore, the weight of incompetence motive should be high in his parameter, accompanied by high value of uncertainty motive too. And the increase value of incompetence motive should be higher than the decrease value of incompetence motive. Hence, the PSI-agent, which will simulate such strategy, will act and look for information to satisfy incompetence motive by satisfying uncertainty motive.

Choosing actions that had positive outcomes enabled the participants, who used balance between motives strategy, to recover from mistakes more quickly than the participants who used other strategies.

5.5.4 Action process:

Participants, who used balance between motives strategy, used more extensive means to apply to a problem and learned how to integrate and synthesize knowledge. Hence, they were very quickly to determine optimal goals when they were encountered to unfamiliar or new locomotions. And that related to their efforts to gather information and to understand the relations between motives and goals in the first session. In other words, that related to their high level of uncertainty motive. They had organized gained information according to solutions, and then they used this information automatically and rapidly. Learning from feed-back was one of their action characteristics. Therefore, they learned from mistakes. They did not stop to learn through their course of action, but rather they enhanced their experiences during the four sessions. So, they quickly responded to changes. Briefly, they were flexible; mentally quick; able to see possibilities; systematic; and adaptable. Table 5.6 shows how the main motive changed during the playing sessions.

Session	Main motive	Action towards satisfying the motive
One	Uncertainty	Exploring new objects and locomotions
Two	Incompetence	Exploring-and then-applying tactic
Three	Task motive	Searching nucleotides
Four	Searching uncertainty because of bore.	Diversive exploration

Table 5.6: The main motive changed during the playing sessions.

(The balance-between-motives-strategy)

5.6 Single Case One- (Participant-XXVIII)'s Strategy (An example of the balance-between-motives-strategy)

5.6.1 Introduction:

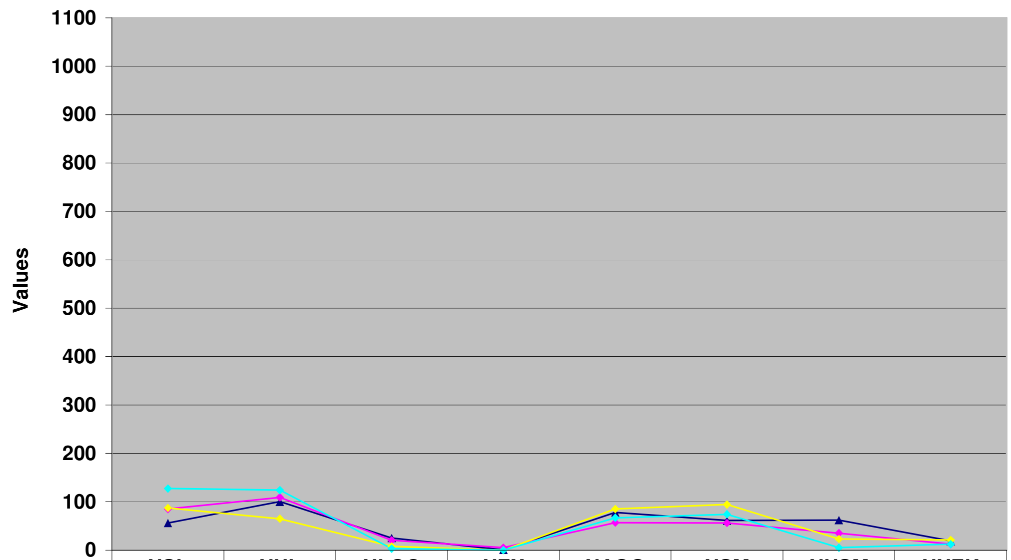
The experimental participant No.28 (female) is a student at the department of psychology at Bamberg University. While she was playing the island game, she made balance between motives. In other words, she made balance between existential needs of the robot and collecting nucleotides. Her motives and the weight of motives changed during the sessions flexibly. That means she was looking for information, in the first session, to satisfy uncertainty motive. In the second session, she applied what she had learned in the first session to satisfy incompetence motive. In the third session, she was doing the task perfectly (i.e., searching "nucleotides") to satisfy nucleotides motive. And finally, diversive exploration was emerged because of bore (see table 5.6).

5.6.2 Action process:

At the beginning, participant No. 28 tried to increase her knowledge span about objects and locomotions. In other words, at the beginning, she had no knowledge or experience about surroundings. Therefore, she had high level of uncertainty accompanied by high selection threshold, especially towards satisfying uncertainty motive. She explored one object in a location, and then she moved from the location quickly. She began first to explore objects by operators. Sometimes a participant began from an operator and tried it with all objects in a location to know the operator function. She explored objects by formulating hypotheses about the relations between objects and operators (e.g. she had chosen one or two operators that could be the right one with the selected object). She was happy when she had a success; especially, when the chosen operator had the right effect. Connections between motives and their goals had success, in first session, except for the damage avoidance goals. Failures, in the first session, did not have big negative effects on her competence, because she considered that failures could be happen at the beginning. She had also high level of uncertainty towards locomotions. Therefore, she explored the directions; however, randomly. Hence, she could not figure out the geographical structure of the island. Her resolution level was low that she could not notice the small differences between objects (i.e., trees). Moreover, she had a good memory to remember the relations between motives, objects and operators. The robot had breakdowns, because of her high level of uncertainty towards locomotions and because she did not know the damage avoidance goals that were always her biggest problem. To some extent, she was sure that she can not put the robot in safe. Once she had found damage avoidance goals, she was very happy and her action began to be steady. At that time, she considered that success is collecting nucleotides parallel to caring about the robot's needs. She began to be always sure that the robot is in a safe situation. So, whenever she had found water, food and plant, she fed the robot. She sometimes fed the robot although the robot did not actually need that. She did not react fast when the robot was in a danger (e.g., when it had damage). However, that increased her arousal and also increased her tendency to contact with affiliation's goal (i.e., Teddy).

Her emotions intensity was somehow moderate and she often smiled when she kissed "Teddy" (Teddy is the goal of affiliation motive). Moreover, she kissed "Teddy", when she had a frustration. It seemed that kissing "Teddy" supported her or increased her competence, especially after failures. She smiled as a reaction to a surprising new object, although the robot was in critical situation. It seemed also as she said to herself, "I am not able to protect the robot so let it and continue exploring the island and search new object". In early two sessions, "Teddy" (the goal of affiliation motive) was an object that satisfied affiliation motive and also for competence. Once she found later that it could be a source of nucleotides, it was one of her favorite objects. As a result, she interacted with "Teddy", whenever she found it.

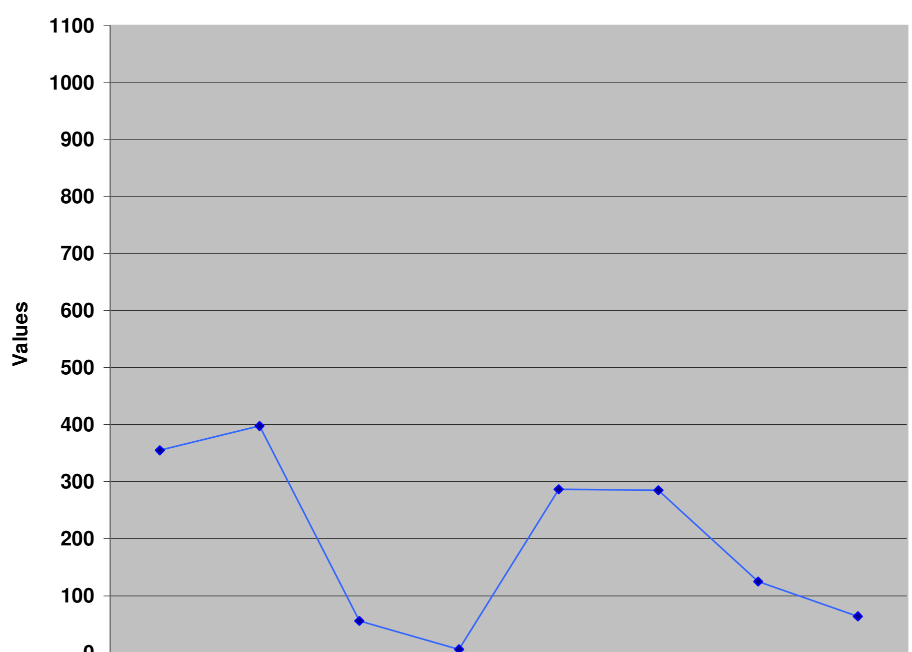
While table 5.7 shows estimated parameters for the experimental sessions, figure 5.23 shows development of action process during the four sessions and figure 5.24 shows profile of her action process. Description of action process of each session will be explained as follow:



	NSL	NUL	NLOC	NEX	NAGG	NSM	NUSM	NNEK
quartile one	56	100	25	1	78	61	62	19
quartile two	85	109	20	5	57	56	35	12
quartile three	87	65	8	0	85	94	23	21
quartile four	127	124	3	0	67	74	5	12

Variables

Figure 5.23: Participant-xxviii
Development of action process during the four sessions.



	NSL	NUL	NLOC	NEX	NAGG	NSM	NUSM	NNEK
Sum of the results	355	398	56	6	287	285	125	64

Variables

Figure 5.24: Participant-xxviii
Profile of the action process.

5.6.3 Participant–xxviii: Session one

Certainty: Because she had high level of uncertainty motive, especially towards objects, she concentrated on exploring objects in the island to increase her knowledge span about operators and objects. At the beginning, she randomly tried one or two operators with an object and that explains why she had got high number of unsuccessful manipulations in this session. After that, she began to formulate hypotheses about objects and operators. Evidently, formulating hypotheses was considered as a type of planning. So, she spent much time in a locomotion and that explains why she had got low number of locomotions. It seems that she had the following concept in her mind;

"Every object in the island has a certain operator that one should find it out".

Selection Threshold: She had a high level of selection threshold towards satisfying uncertainty motive. As well, collecting "nucleotides" was considered as sub-goal. Moreover, she had low resolution level and she could not discriminate between objects that had small difference (i.e., trees)

Goal–Elaboration: She spent much time to elaborate goals and consequently; the relations between motives and their goals was structured, except for damage avoidance goals.

Competence: At the beginning, she had no experience and knowledge about objects, operators and locomotions of the island. So, she had high level of uncertainty. Consequently, she had a high level of incompetence. To increase her level of competence she used exploring-applying tactic (see figure 5.25) in which she applied what she had learned about objects and operators whenever she met a known object. After that, she turned to explore a new object. **Arousal:** She had moderate level of arousal and that was noticeably observed as she had put her initial hypothesis to test. Furthermore, a surprising emotion to effects of the operators on objects plainly remarked her reactions in this session.

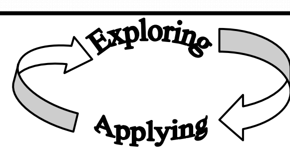


Figure 5.25: Exploring- applying tactic.

5.6.4 Participant-xxviii: Session two

Certainty: she had high level of uncertainty motive; especially towards locomotions. Therefore, she concentrated on exploring locomotions in the island to increase her knowledge span about locomotions of the island. And to satisfy this motive, she moved continually between locomotions; and as a result, she had got very high number of successful locomotions in this session. However, she did not build a geographical map for the island. Consequently, in this session, she had got a high number of unsuccessful locomotions.

Selection Threshold: She had a high level of selection threshold particularly towards satisfying uncertainty motive. This persistence caused the robot to have damage because the robot had been encountered to harmful locomotions. In addition, she did not know damage avoidance's goals; so, the robot had frequently breakdowns.

Resolution Level: In this session, she had low resolution level and she could not discriminate between objects that had small differences.

Competence: To increase her competence after the robot had broken-down; she tried to collect "nucleotides" as possible as she could. Furthermore, she reused "exploring-applying strategy" to increase her competence; however, she zoomed in an object followed by zooming out without taking action. As well, moving randomly among locomotions without zooming objects was observed under low level of competence.

Arousal: She had high level of arousal because of frequent breakdowns and that had affected her planning negatively. For example, she got tensional and could not successfully move among locomotions; therefore, she had high number of unsuccessful locomotion. Furthermore, distress and sad emotions appeared on her face in this session accompanied by red face.

Action style: This session was remarkably characterized by her persistence and patience to do well as possible (i.e.; collecting "nucleotides"), although the situation of the robot was frustrating.

5.6.5 Participant-xxviii: Session three

Main motive: While collecting “nucleotides” was her main motive in this session, searching goals of existential needs was constantly considered her sub-goal. For these reasons, she had collected very high number of “nucleotides” and the robot did not breakdown in comparison to the two early sessions. In addition, she frequently kissed “Teddy” (the goal of affiliation motive) whenever she found it after every success. It seemed that contact with affiliation’s goal was regarded as a reward because of success. Additionally, one should note that contacting with affiliation’s goal, in this session, was greatly needed after success.

Certainty: She had a moderate level towards satisfying uncertainty motive, because she had got most information about objects and locomotion in the previous tow sessions. Furthermore, because she had had collected many “nucleotides”, her competence was increased and was very high in this session.

Selection Threshold: Her selection threshold was moderate. Hence, collecting “nucleotides” and searching existential goals were balanced.

Basic reinforcement strength: Because she steadily and progressively acted and goals were successfully chosen in respect to their motives, strong and robust links between motives and goals characterized her basic reinforcement strength in this session. Resolution level was low and she could not discriminate between objects that had small differences.

Action style: We can confidently say that her success in the third session was related to the successful exploration process that she had made in the first two sessions. For example, her high level of uncertainty towards objects in the first session powered her to gain knowledge about objects in the island. Moreover, her high level of uncertainty motive towards the island locomotions motivated her to have an experience about locomotions in the island. Therefore, her action ,in the third session, was automatic and routine (applying perfectly what she had learned). Moreover, happiness emotion appeared after she had recognized damage-avoidance goal.

5.6.6 Participant-XXVIII: Session four

Action style: Figure 5.26 shows her action style in this session. This session was characterized by:

- Applying all gained knowledge to collect many "nucleotides" as possible.
- Supplying "James" with existential goals, although that was absolutely unnecessary because the robot motivation was low (supply at low motivation). Over-supplying the robot with existential goals was a source to increase her competence.
- Bore that was caused by high level of certainty accompanied by high level of competence.
- Re-exploring known objects by new operators. As a result, she had high number of unsuccessful manipulations. As well, because of bore, she moved between locomotions. Consequently, she had high number of unsuccessful locomotions.
- Low resolution level and low level of selection threshold; consequently, there was no main goal in this session rather than all goals had similar chance to be the target of action.
- Because of bore, she searched uncertainty. Therefore, number of successful locomotions and number of unsuccessful locomotions were very high.
- Bore had increased her tendency towards searching affiliations goal. Hence, in this session, "Teddy" (the goal of affiliation motive) was searched and kissed frequently. Moreover, basic reinforcement strength between motives, goals and operators was strong and robust.

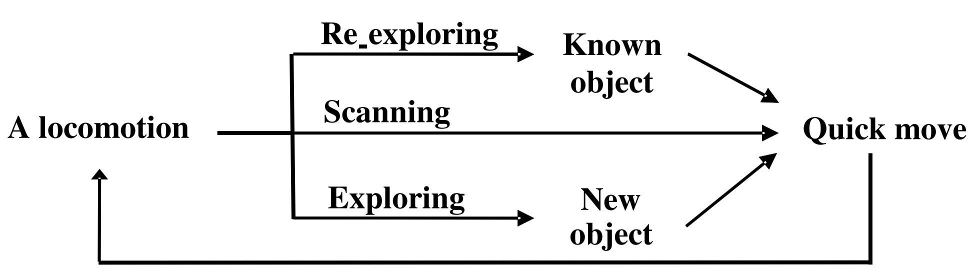


Figure 5.26: Participant-xxviii (Session four: action style).

Motives	Weight				Increase				Decrease			
Sessions	1	2	3	4	1	2	3	4	1	2	3	4
Existential	Low	Low	Moderate	High	Low	Low	Moderate	High	High	High	Moderate	Low
Uncertainty	High	High	Moderate	High	High	High	Moderate	High	Low	Low	Moderate	Low
Incompetence	Moderate	Moderate	High	High	Low	High	High	High	High	Moderate	High	Low
Affiliation	V. Low	V. Low	Low	High	V. Low	V. Low	Low	High	High	High	Moderate	Low
Nucleotides	Low	Moderate	High	High	Low	Moderate	High	High	High	Moderate	V. Low	Low
S. Threshold	V. High	High	Moderate	Low								
R. Level	Low	Low	Low	Low								
Arousal	Moderate	High	Moderate	High								

Table 5.7: Participant-xxviii–estimated parameters for the experimental sessions.

5.7 Single Case Two- (Participant-XXXVIII)'s Strategy (An example of the stereotype-strategy)

5.7.1 Introduction:

The experimental participant No.38 (female) is a student at the department of psychology at Bamberg University. While she played the island game, her action style was classified as stereotype-strategy. Figure 5.28 shows development of action process during the four sessions and figure 5.29 shows profile of her action process. Table 5.8 shows estimated parameters for the experimental sessions. The description of her strategy will be discussed as follow.

5.7.2 Uncertainty motive:

Participant No.38 had most of the time very high level of uncertainty motive; especially towards exploring objects. Therefore, she tried to explore the most objects in locomotion by the most operators in the operators' list. However, she did not have success, because she did not formulate hypotheses about both objects and operators, but she had used random tactics to explore objects all the time. Consequently, she had high number of unsuccessful manipulations. In general, those who used stereotype strategy did not change or develop their learning tactics during the playing sessions and were intolerant to look for new information, or increase their capabilities and expand their knowledge. While those who used balance between motives strategy continued to seek new information and persistently attempt to enhance their abilities and skills to control environment and to increase their knowledge span. Participants, who used stereotype-strategy, had used the following tactics to satisfy uncertainty (see figure 5.27):

A. Randomly exploring objects and operators:

Participants did not build hypotheses about objects and their relations to motives, but they had randomly explored objects. To clarify, an object was zoomed in, and then an operator was randomly activated from operators' list. Whatever the operator had effect or not, the object was zoomed out. Hence, action's profile of such participants was characterized by high number of aggressions, high number of unsuccessful manipulations and few number of successful manipulations. That because the subject weakly stored the object and its operator in memory. Moreover, subject's competence was decreased by such repeatedly failures.

B. Randomly exploring geographical structure of the island:

Participants, who used stereotype-strategy, did not build hypotheses about geographical structure of the island; but they had explored directions randomly from directions' list. Consequently, action's profile of such participant was characterized by high number of unsuccessful locomotions.

Participant No. 38 simply refused to search new knowledge and insisted on refusing to investigate how to know. She spent her research time gaining information that could support what she had already gained at the first stage of playing. She was inflexible to consider anything else than what she had predetermined and categorized, and she did not attempt to re-examine her learning tactic, or get accurate information about the relations between objects and operations and/or objects and motives.

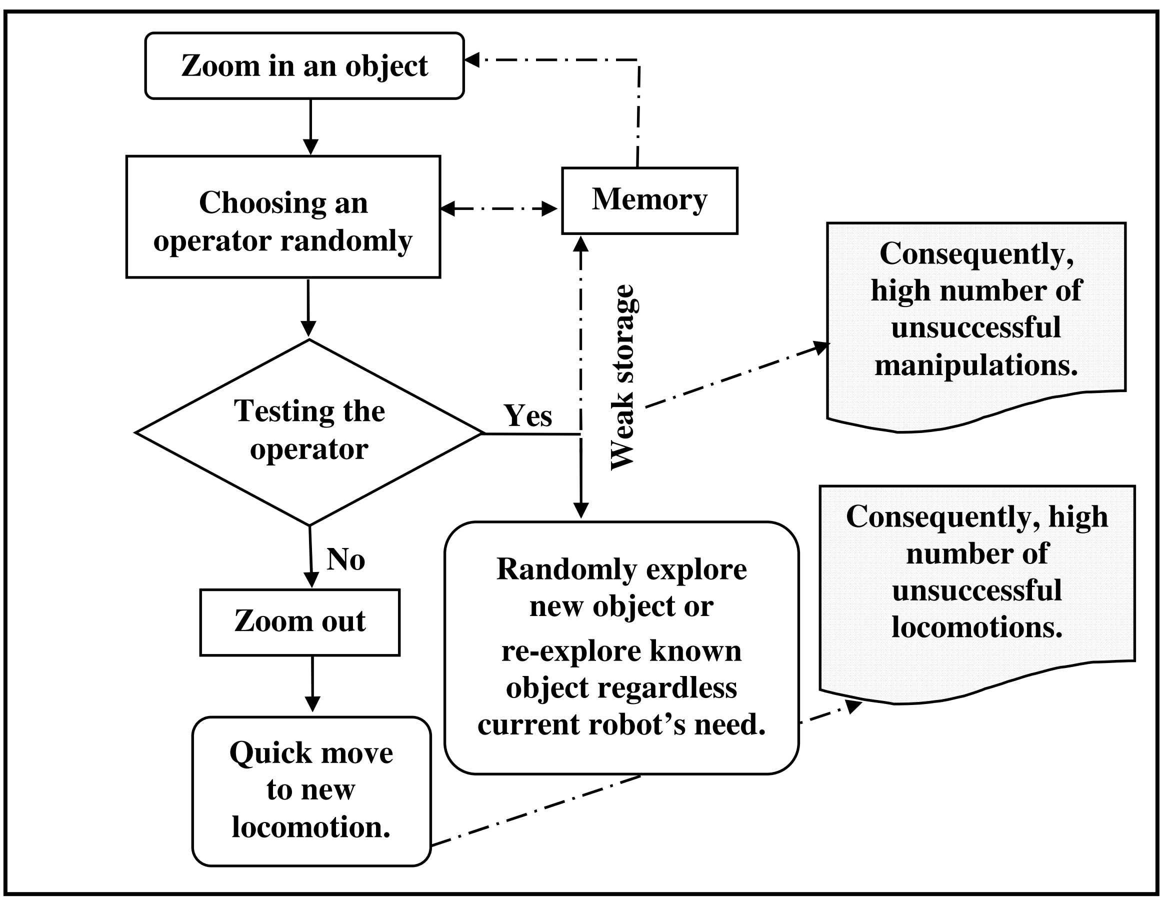
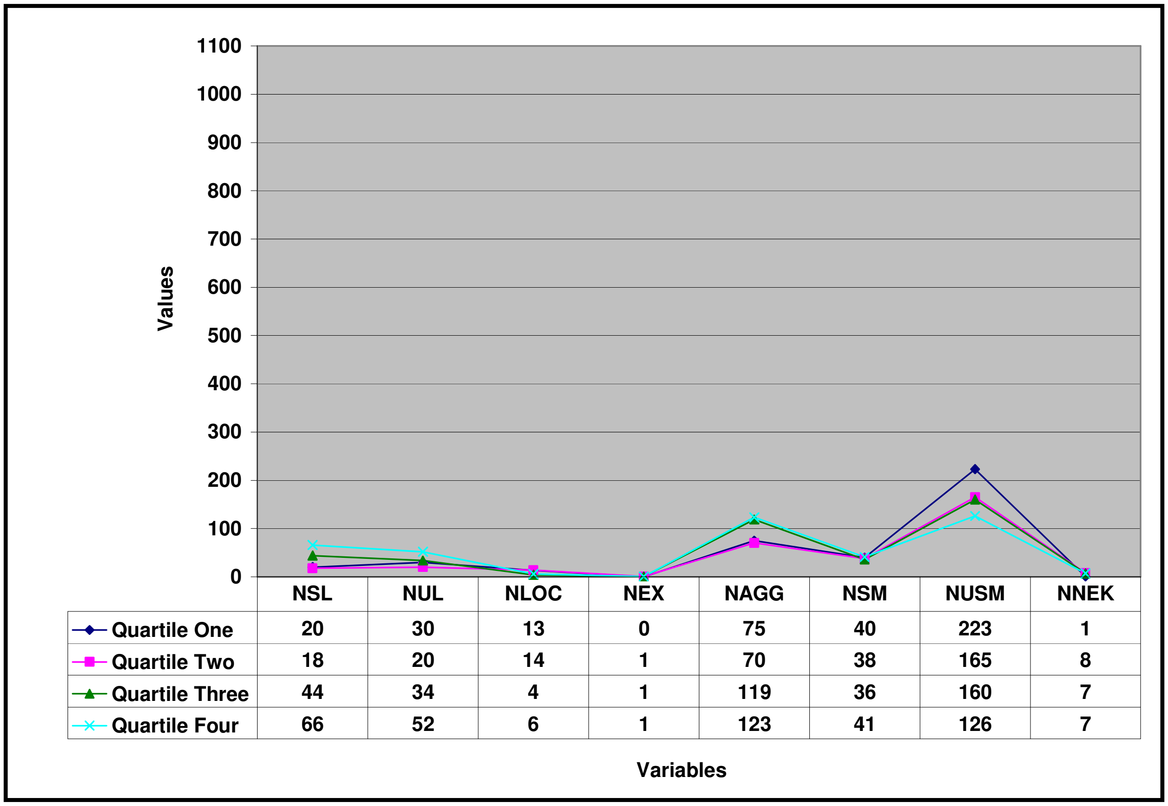
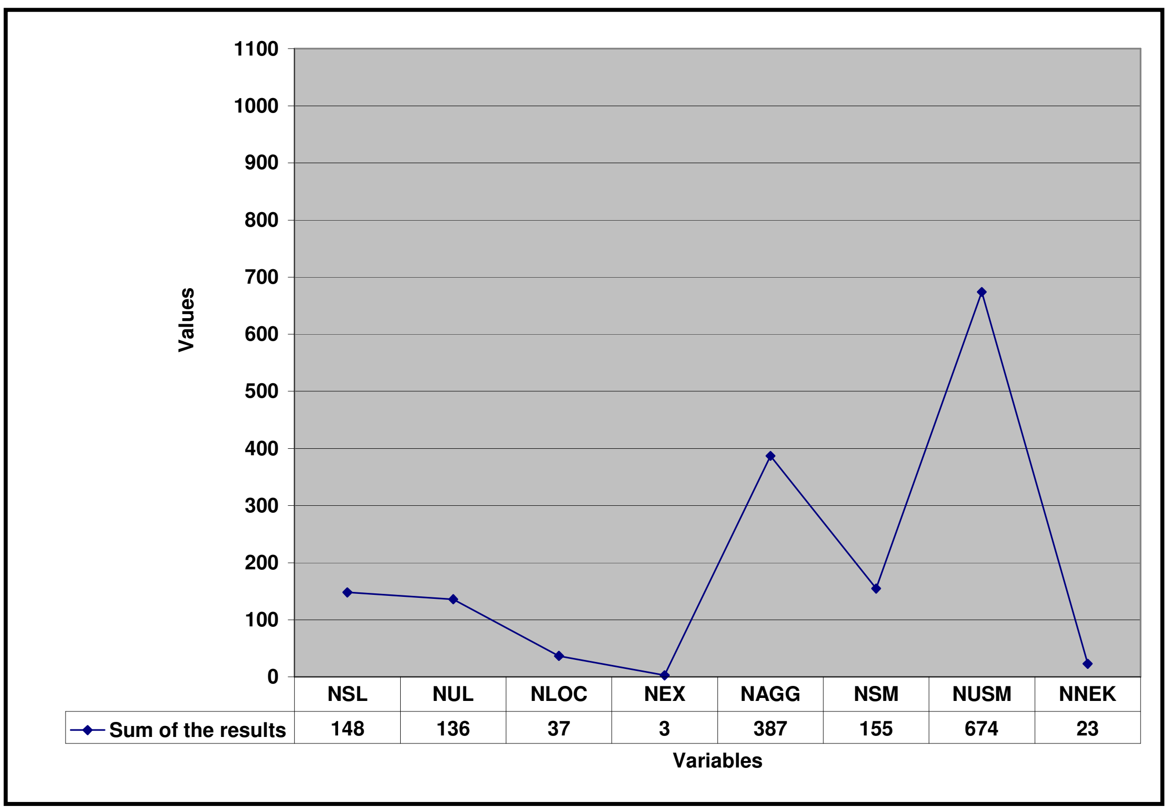


Figure 5.27: Participant-xxxviii-action process. (stereotype-strategy).



	NSL	NUL	NLOC	NEX	NAGG	NSM	NUSM	NNEK
Quartile One	20	30	13	0	75	40	223	1
Quartile Two	18	20	14	1	70	38	165	8
Quartile Three	44	34	4	1	119	36	160	7
Quartile Four	66	52	6	1	123	41	126	7

Figure 5.28: Participant-xxxviii.
Development of action process during the four sessions.



	NSL	NUL	NLOC	NEX	NAGG	NSM	NUSM	NNEK
Sum of the results	148	136	37	3	387	155	674	23

Figure 5.29: Participant-xxxviii
Profile of the action process.

5.7.3 Goal-elaboration:

Goal-elaboration process was failed because she had low level of basic reinforcement strength. Hence, she quickly forgot what she had learned and explored and her knowledge span about objects and the function of operators was very narrow. Consequently, she had got a very high number of unsuccessful manipulations. As well, those who used stereotype strategy during playing the island game did not strive to improve or meet a standard of excellence during the playing or to find ways to do better, because they just depended on the physical senses of objects (i.e., dunes and rocks). For instance, participant No. 38 did not explore intensively dunes and rocks. Although tactics should work together to achieve the ultimate goal that one wants to achieve, some participants did not look at their tactics as an integrated sequence, and therefore long-term effects were not considered. For example, sometimes the robot had massive damage; however, she began to collect nucleotides. Consequently, the robot was broken-down and she lost five nucleotides, although he had taken this risk to collect two nucleotides.

5.7.4 Incompetence motive:

Participant No. 38 had a low level of incompetence motive and she was always hesitated and incompetent (e.g., she zoomed in objects, and then zoomed out without any action and that could explain why she had a high number of aggressions). She tried very carefully and for a long time before she could decide an action. She hardly smiled during playing the game. When the consequence of using an operator had no effect, she was quickly frustrated and her competence decreased quickly; therefore she switched quickly between directions (back and front), operators, and objects.

Those who used stereotype strategy were unconfident, because all they had to do was just repeating routine and acted in a stereotype manner. For example, they sometimes moved between locomotions without real exploration purpose and because of this, time passed without benefit. In addition, she was reacting uncontrollably, inhibiting quickly and ignoring the robot existential needs.

5.7.5 Selection threshold:

She had a high level of selection threshold towards satisfying uncertainty motive especially towards exploring objects. Moreover, sub-goals were not sometimes considered. She was relatively making stereotype generalization about the function of operators and her responses were automatic and routine. For example, sieving operator was hardly used while shaking operator was frequently and routinely used with most objects. High selection thresholds of those who used stereotype strategy kept their stereotype performances always domain (e.g., they were not careful to define long-term planning, determining and setting goals, and a careful consideration of the consequences of actions, but they were rather actionism. Participants, who used stereotype strategy, would be less likely to change their stereotype strategy whatever the result of exploration process indicates that they were in a wrong direction.

5.7.6 Action process:

As her action rhythmus was slow and she did not encounter the robot to harmful locomotions unintentionally, the robot did not lose much energy. Therefore, her robot did not need food, water, or energy more than usual. So, that explained why her robot had few number of breakdowns. She had high level of arousal and a very low level of basic reinforcement strength and that was obviously observed as she had always forgot the connection between objects and their operators.

Since her planning was unsuccessful and her concentration was useless because of the high level of arousal, she frequently showed frustration emotion during playing the game. That was because she acted from fear of failure instead of hope of success. Hence, her emotions were mixed between worry and fear which led to rigid planning that did not allow any detours of the planned course of action to appear; so planning was incoherence. This inability to manage distressing emotions (i.e., worry and fear) led to shallow planning especially under time pressure.

She spent much time in a locomotion and that could explain why she had got few number of locomotions in the first session. Under stress, she adopted again the same short-term strategy to avoid the problem and she seemed incapable of making a single positive step towards changing her action. Her stereotype action was dominant and unchangeable during the four playing sessions and that might be because she was not aware why she reacted the way she did (she simply had no self reflection). Moreover, she did not learn from feed-back or previous experiences. Therefore, her responses seemed reflexive or mechanical without thinking. Her responses were reflexive because she did not think deliberatively and so there was no continuous learning development process, but rather separate reflexive learning units. And because she also did not formulate hypotheses while she was planning, her actions seemed impulsive and hasty. After a short period of successful actions, her performance was relapsed and slipped and mistakes appeared again.

Since participants, who used stereotype strategy, were not comfortable with new information (e.g., they did not want to update their information; did not open to seek out original view from a wide variety of sources; could not generate new ideas and take different perspectives; did not seize opportunities and risks in their thinking; i.e., set challenging goals and take calculated risks), their robot had breakdowns because they did not try to fulfill the robot's needs or seek ways to satisfy these needs.

Motives	Weight				Increase				Decrease			
Sessions	1	2	3	4	1	2	3	4	1	2	3	4
Existential	V. Low	Low	V. Low	V. Low	V. Low	Low	V. Low	V. Low	Low	Low	V. Low	V. Low
Uncertainty	High	High	Moderate	High	High	High	High	High	Low	Low	Low	Low
Incompetence	Low	Low	Moderate	Moderate	Low	Moderate	Moderate	Moderate	Moderate	Moderate	Low	Low
Affiliation	V. Low	V. Low	V. Low	V. Low	V. Low	V. Low	V. Low	V. Low	V. Low	V. Low	V. Low	V. Low
Nucleotides	Low	Low	Moderate	Moderate	Low	Low	Moderate	Moderate	High	Low	Low	Low
S. Threshold	V. High	High	Moderate	Moderate								
R. Level	V. Low	V. Low	Low	Low								
Arousal	High	Moderate	Moderate	Moderate								

Table 5.8: Participant-xxxviii–estimated parameters for the experimental sessions.

Conclusion

In this chapter, we have aimed to investigate different action strategies of subjects that they used during handling a complex task. We have approached our task mindful by an experiment. Therefore, we have firstly demonstrated the experiment and the experimental design and procedure (i.e., participants, materials, the island-game, apparatus, instructions, and dependent variables. Secondly, we have discussed the results of the experiment, which indicated that there were four strategies and many different tactics that had been applied by the participants while playing the island game.

These strategies were the nucleotides-first-strategy, the survival-strategy, the balance-between-motives-strategy, and the stereotype-strategy. We have described the action process of each strategy (i.e. uncertainty motive, incompetence motive, nucleotides motive, existential needs, resolution level and selection threshold) in perspective of the PSI-approach. Moreover, we have illustrated advantage and disadvantage of each strategy and the most important parameters to simulate these strategies. We have also explained most tactics that had been used during playing the game (e.g., formulating hypotheses about objects and operators before acting, clockwise direction tactic, complete-incomplete action-tactic, bipolar-direction-tactic, and randomly exploring objects and operators tactic).

In next chapter, we will show how we simulate these strategies, in perspective of the PSI-theory and by PSI-agent, and the two single cases that had been discussed in this chapter. Furthermore, we will discuss the behaviour of the PSI-and and we will also evaluate this behaviour in corresponding to major agent criteria that have been shown in chapter three.

Chapter

6

Simulation, Results and Discussion

Summary

In this chapter, we are going to discuss how we simulated human action strategies by the PSI-agent. In section 6.1 we will distinguish between the four different action strategies which were used by the participant when playing the island game. In section 6.2 we are going to explain how we simulated these four different action strategies and the action strategies of two single cases. Correlations between the results of participants' action processes and the results for different sets of parameters by PSI-agent will be explained in section 6.3. In Section 4.4 we will discuss these correlations and we will evaluate the behaviour of the PSI-agent with respect to the agent-criteria which were discussed in chapter three (see 3.4, p. 90). Work in progress will be shown in section 6.5. Finally, we will conclude this work with a summary and an outlook towards future work.

6.1 Action Strategies: Categorization

6.1.1 Introduction:

In chapter five, we described four strategies which the participants used when they played the island game. In this section we are going to show the differences between these strategies and how many participants used these strategies.

6.1.2 One situation but four different action strategies:

In this section, we are going to distinguish between the four different strategies. Figure 6.1 illustrates an example of a state of the existential needs of the robot. As illustrated in figure 6.1, the thirst motive is an urgent motive and after a while the damage avoidance motive may also be urgent. Figure 6.2 (see below-left side) shows a screenshot of a location on the island. And we can see some goals for the motives in this location. A participant can manipulate these goals to satisfy the robot's needs. We will explain how participants with different strategies respond to such a situation:

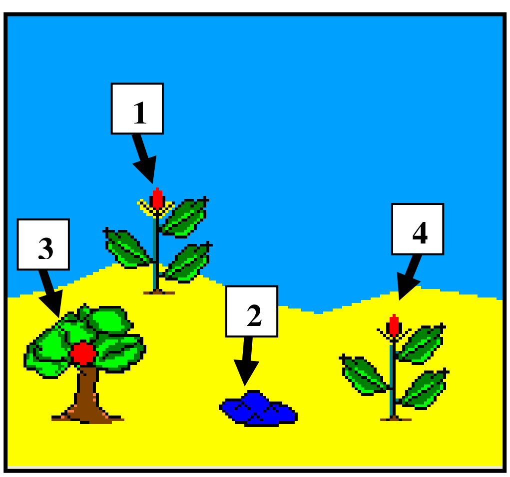


Figure 6.2:
A screenshot of a location in the island (we see here some goals of the motives).

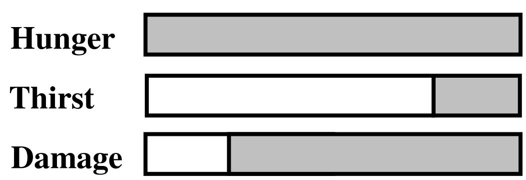


Figure 6.1:
An example of a state of the existential needs of the robot.

N.	Goal
1	Damage avoidance motive.
2	Thirst motive.
3	Task motive (i.e. collecting the nucleotides).
4	Damage avoidance motive.

Table 6.1:
Goals of the motives.

The survival-strategy	The main goal of the participants who use the survival-strategy is to care for the robot and assure its security by satisfying its existential needs. Therefore, those participants look for goals for the existential needs of the robot. That is accompanied by high selection threshold. Nucleotides are ignored. A participant who uses the survival strategy acts in such situations as follows: Firstly, the participant activates the “sucker operator” in order to suck water (object-Nr. 2.) to satisfy the thirst motive, because this motive is an urgent motive in this situation. Secondly, the participant would choose a plant that is considered as a goal of the damage avoidance motive (object-Nr.1 or Nr. 4) to feed the robot, although damage is not very high in this situation as shown in figure 6.1 (p.200). The participant uses over-feed tactic because he/she expects that the damage avoidance motive would increase. Thirdly, if the participant has a high level of the task motive (i.e. collecting the nucleotides), he would explore the tree (object-Nr.3) to look for nucleotides. If the participant has a low level of the task motive, he would quickly move from the current location to a new one. If one of the existential motives of the robot increases, he quickly moves from the current location to a new one to look for goals of the existential needs of the robot. Briefly, the participant would attempt to protect the robot as possible and he would have advantage to ignore the task motive.
The nucleotides-first-strategy	The main goal of the participants who use the nucleotides-first-strategy is to collect as many nucleotides as possible. Collecting the nucleotides is the main goal. That is accompanied by high selection threshold in order to collect the nucleotides. Moreover, the existential needs of the robot are mostly ignored. A participant who uses the nucleotides-first-strategy acts in such situations as follows: Firstly, the participant would explore the tree (object-Nr.3) to look for nucleotides in order to satisfy this motive (i.e. the task motive). Secondly, if the participant finds a nucleotide, he would collect it. And if his task motive is satisfied, he would activate the “sucker operator” to suck water (object-Nr.2) in order to satisfy the thirst motive, because the thirst motive is an urgent motive. If the participant does not find a nucleotide, his task motive (i.e. collecting the nucleotides) would be still high. Therefore, the participant would quickly move to new location to look for other nucleotides. Although the thirst motive is an urgent motive in this situation as shown in figure 6.1 (p. 200) and the damage avoidance motive would increase after a while; however, the participant would leave the location to look for other nucleotides. Briefly, the participant would attempt to collect as many nucleotides as possible and would ignore the existential needs of the robot.

The stereotype-strategy	Participants who use the stereotype-strategy have actually no main goal; all goals of the different motives are considered. That is accompanied by a low selection threshold as well as a low level of basic reinforcement strength. A participant who uses the stereotype-strategy acts in such situations as follows: Firstly, the participant would explore a plant (object-Nr.1 or Nr. 4) which is considered as a goal of the damage avoidance motive, although the damage motive is not the most urgent motive in this situation. The participant explores the island not with the intention to feed the robot, but to satisfy the uncertainty motive. However, the participant would not store the results of the exploration in his memory; consequently, he would repeat the same operation in future. That is because the participant has a low level of basic reinforcement strength. Secondly, the participant would attempt to activate the “sucker operator”. However, because of a lack of competence he would not use it and then he would zoom away from the object (i.e., object-Nr. 2.). Under all conditions (success or failure), the participant would attempt to explore the other plant (object- Nr.1 or Nr.4) randomly. Finally, the participant would leave the location to another one without determining exactly an explicit goal for the next exploration. In other words, the participant began to explore goals randomly with very low level of basic reinforcement strength and then moved to a new location without knowing exactly what he/she should look for. Briefly, the participant would ignore both tasks (i.e., the robot’s needs and the task motive).
The balance-between-motives-strategy	Participants who use the balance-between-motives-strategy give equal weights to the task motive (i.e. collecting the nucleotides) and the robot’s needs. That is accompanied by a moderate (medium) level of the selection threshold and a high level of the basic reinforcement strength. A participant who uses the balance-between-motives-strategy acts in such situations as follows: Firstly, the participant would quickly activate the “sucker operator” to suck water (object-Nr.2.) in order to protect the robot from a breakdown. Secondly, the participant would zoom in to the tree (object-Nr.3) to look for nucleotides in order to satisfy the task motive. Thirdly, the participant would choose a plant (object-Nr.1 or Nr. 4) that is considered as a goal of the damage avoidance motive in order to feed the robot, although the damage is not very high in this situation but the thirst motive as shown in figure 6.1 (p.201). The participant would do that to ensure the robot’s safety, when he/she moves to new location. Finally, the participant would quickly move to new location in order to look for nucleotides. Briefly, the participant would attempt to protect the robot as possible and at the same time to collect nucleotides.

6.1.3 Discussion

As discussed in chapter five, the results of the experiment show that there are no differences between the results of the participants of group-A* and the results of the participants of group-B** with respect to the eight dependent variables*** and that because the participants had played the game using different strategies. Therefore, we can assume that in this case the type of environment, whether poor or rich, plays no important role. Most important is the way (the strategy) the available resources are managed by the actors. As shown in figures 6.5 and 6.6 (p. 207), there is no difference between the mean of nucleotides for the participants of group-(A) (i.e., M = 81.95) and the mean of nucleotides for the participants of group-(B) (i.e., M =84.85).

The mean of breakdowns for the participants of group-(B) (i.e. M= 8.2) was higher than the mean of breakdowns for the participants of group-(A) (i.e. M= 4.45) as shown in figures 6.5 and 6.6 (p. 207). The reason for this result is that the participants of group-B played the non-renewable resources version of the game, while the participants of group-A played the renewable resources version of the island-game.

In figures 6.7 and 6.8 (p. 208), we see the results of the subjects with the four different strategies with respect to the eight dependent variables for the whole sample (n=40). Participants who used the nucleotides-first-strategy had the highest number of successful manipulations, because they had a high motive to collect as many nucleotides as possible. Moreover, Participants who used the nucleotides-first-strategy concentrated on just those objects which included nucleotides and ignored the existential needs; consequently, they had also the highest number of locomotions and the highest number of breakdowns.

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* The participants of group-A played the renewable resources version of the island-game. For further details see chapter five — 5.1.7, p. 153.

** the participants of group-B played the non-renewable resources version of the game. For further details see chapter five — 5.1.7, p. 153.

*** The eight dependent variables were defined in chapter five (5.1.8, p. 154).

Participants who used the stereotype-strategy had the lowest number of successful manipulations, because they had the lowest basic reinforcement strength. Therefore, they quickly forgot what they had learned. Consequently, they had the lowest number of collected nucleotides. Moreover, participants who used the stereotype-strategy had a high number of unsuccessful manipulations, a high number of unsuccessful locomotions and a high number of breakdowns.

As shown in table 6.2 (p. 205), most of the participants used the balance-between-motive-strategy or the nucleotides-first-strategy when playing the island game.

Since the task motive (i.e. collecting the nucleotides) was the main motive of participants who used the nucleotides-first-strategy and the task motive was also one of the main motives of participants who used the balance-between-motive-strategy, it can be assumed that the common factor between these two strategies was the task motive (i.e. collecting the nucleotides). When we look for the background of the task motive, we could assume that the task motive is based on achievement motivation. I assume that the participants' motives were affected by their cultural values. And since social values (from the author's point of view) refer to the criteria which determine forms of the actions and provide an important filter for selecting input, especially motives orders. I assume that the actions of the participants in this game were affected by "the feeling of responsibility towards work" as a social value in the German culture. This result indicates that most of the participants had a high level of the task motive (i.e. collecting the nucleotides), because they were affected by "the feeling of responsibility towards work" as a social value in the German culture.

Strategies	Nucleotides first	Balance	Survival	Stereotype	Sum
Group-A	6	8	4	2	20
Group-B	8	8	1	3	20
Sample	14	16	5	5	40

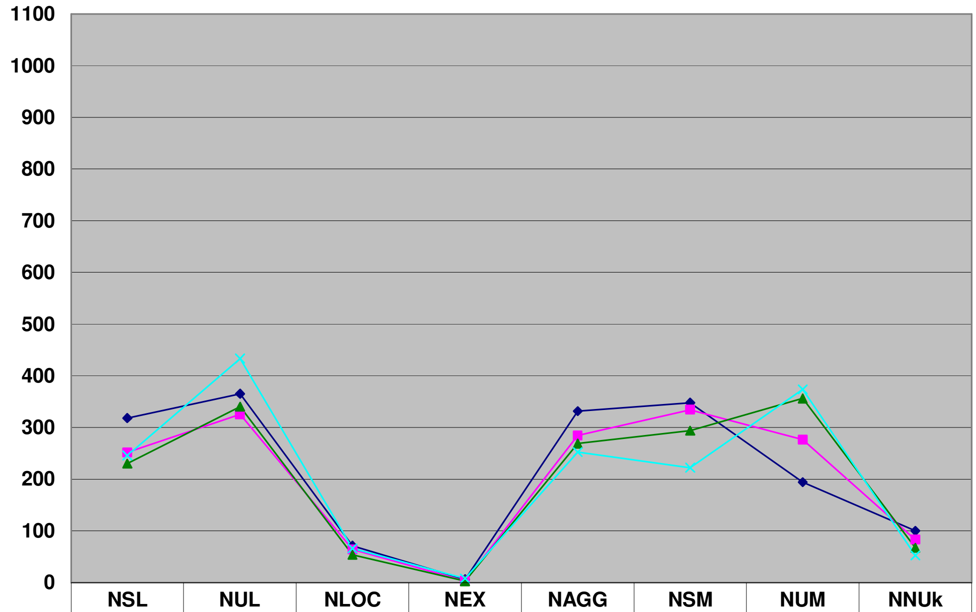
Table 6.2: The four strategies and the number of subjects who used these strategies.

	Nucleotides first		Balance		Survival		Stereotype	
Group	"A"	"B"	"A"	"B"	"A"	"B"	"A"	"B"
NSL	318.33	291.5	251.88	253.5	230	252	246	267
NUL	365.33	388.88	325.25	342	340	265	433.5	329
NLOC	71.33	77.13	64.38	64.13	53.5	56	66	44.33
NEX	6.17	10.25	3.13	7.25	2.75	3	8	7
NAGG	331.67	282.5	284.63	248.75	269	315	252.5	277.67
NSM	348.17	389.33	334.13	279.13	294	283	222.5	210.33
NUM	194.17	317.5	276.33	256.13	356.25	449	374	325.67
NNUK	100	110.63	83.13	76.88	67.25	75	52.5	40.67

Table 6.3: Means of the dependent variables for each group and for each strategy.

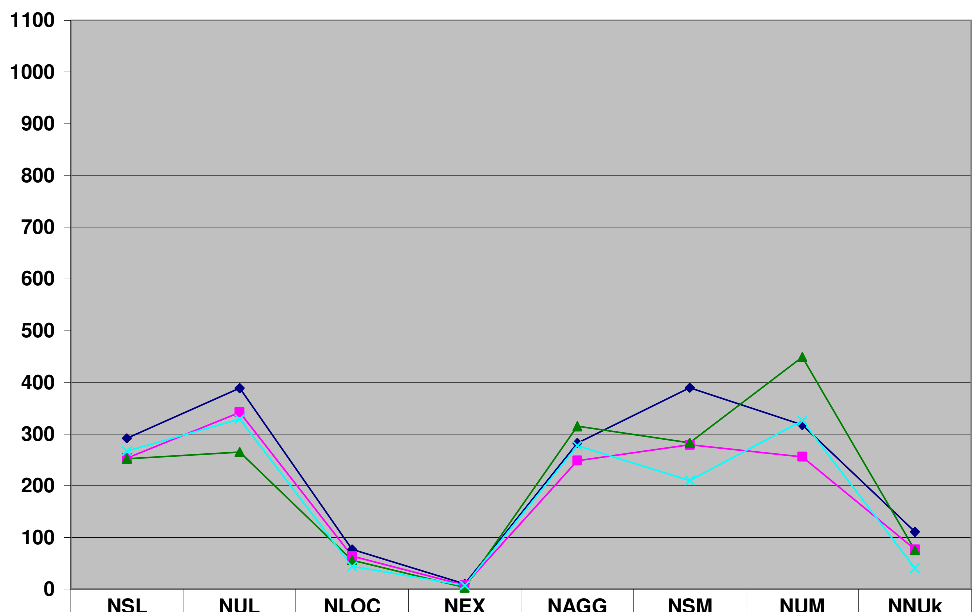
	Nucleotides first		Balance		Survival		Stereotype	
	M	SD	M	SD	M	SD	M	SD
NSL	303	77.3	252.69	62.51	234.4	20.6	258.6	79.93
NUL	378.79	105.59	333.63	98.26	325	62.07	370.8	139.5
NLOC	74.64	14.48	64.25	10.93	54	4.95	53	12.79
NEX	8.5	3.23	5.19	3.06	2.8	0.83	7.4	3.36
NAGG	303.57	49.24	266.69	32.56	278.2	33.17	267.6	75.57
NSM	371.71	110.49	306.63	45.99	291.8	11.52	215.2	53.14
NUM	264.64	234.91	266.25	115.27	374.8	80.48	345	218.65
NNUK	106.07	20.04	80	12.99	68.8	6.14	45.4	15.4

Table 6.4: Means and standard deviations for the whole sample (n=40).



	NSL	NUL	NLOC	NEX	NAGG	NSM	NUM	NNUk
Nucleotides first	318.33	365.33	71.33	6.17	331.67	348.17	194.17	100
Balance	251.88	325.25	64.38	3.13	284.63	334.13	276.33	83.13
Survival	230	340	53.5	2.75	269	294	356.25	67.25
Stereotype	246	433.5	66	8	252.5	222.5	374	52.5

Figure 6.3: Profiles of the four different strategies–group-A (n=20).



	NSL	NUL	NLOC	NEX	NAGG	NSM	NUM	NNUk
Nucleotides first	291.5	388.88	77.13	10.25	282.5	389.33	317.5	110.63
Balance	253.5	342	64.13	7.25	248.75	279.13	256.13	76.88
Survival	252	265	56	3	315	283	449	75
Stereotype	267	329	44.33	7	277.67	210.33	325.67	40.67

Figure 6.4: Profiles of the four different strategies–group-B (n=20).

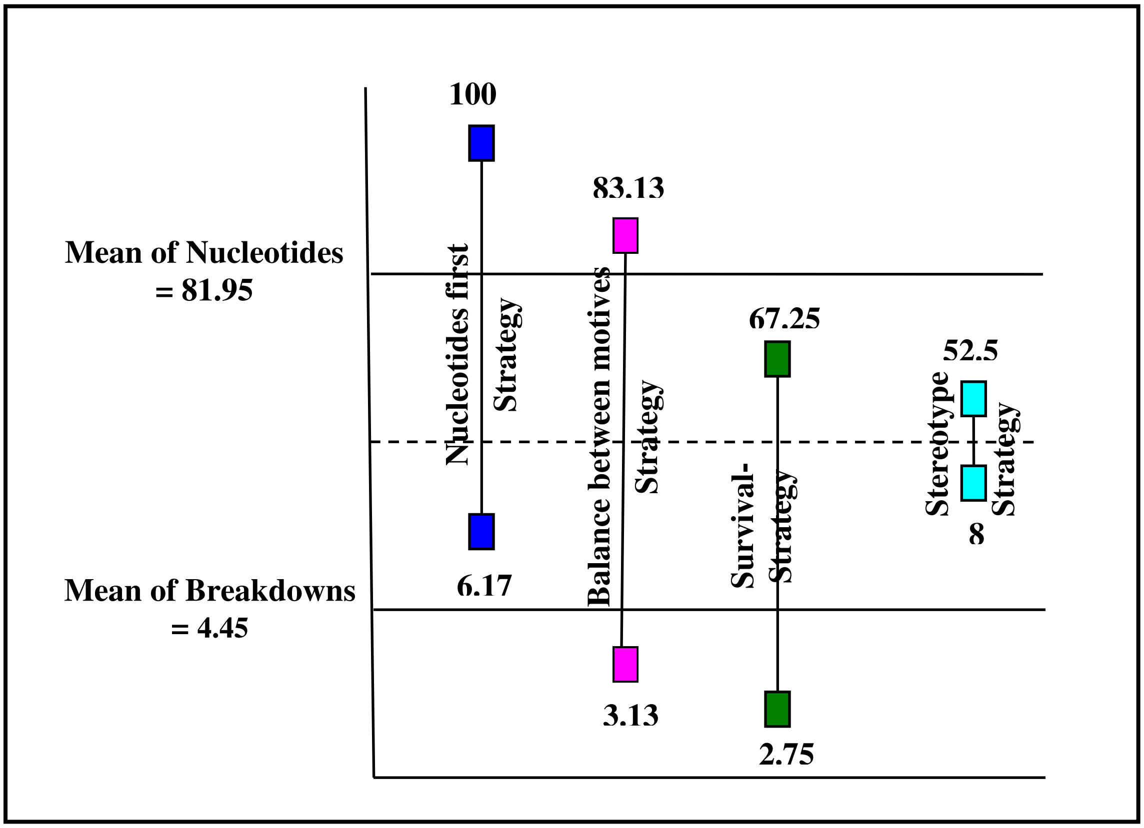


Figure 6.5: A comparison between the four different strategies "group-A" (n=20).

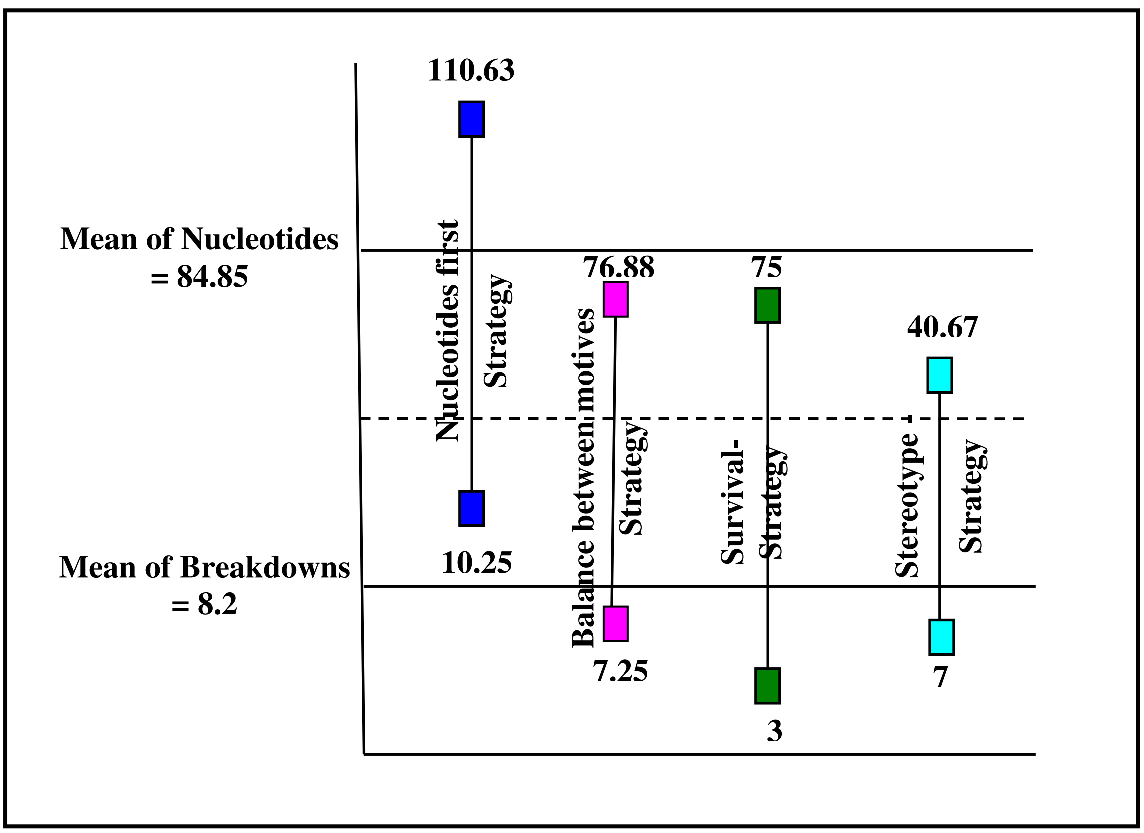
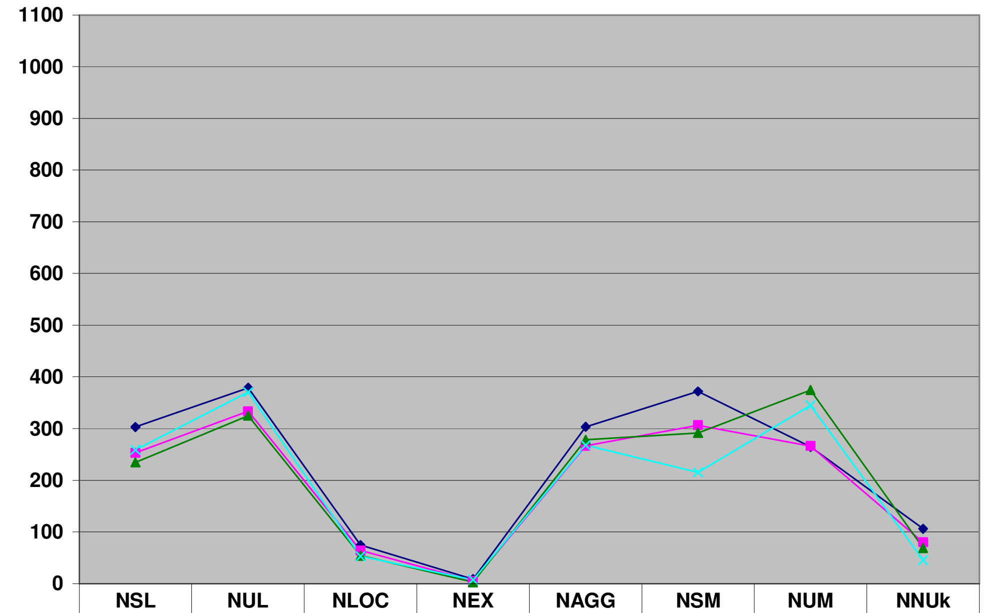


Figure 6.6: A comparison between the four different strategies "group-B" (n=20).



	NSL	NUL	NLOC	NEX	NAGG	NSM	NUM	NNUk
Nucleotides first	303	378.79	74.64	8.5	303.57	371.71	264.64	106.07
Balance	252.69	333.63	64.25	5.19	266.69	306.63	266.25	80
Survival	234.4	325	54	2.8	278.2	291.8	374.8	68.8
Stereotype	258.6	370.8	53	7.4	267.6	215.2	345	45.4

Figure 6.7: Profiles of the four different strategies–the whole sample (n=40).

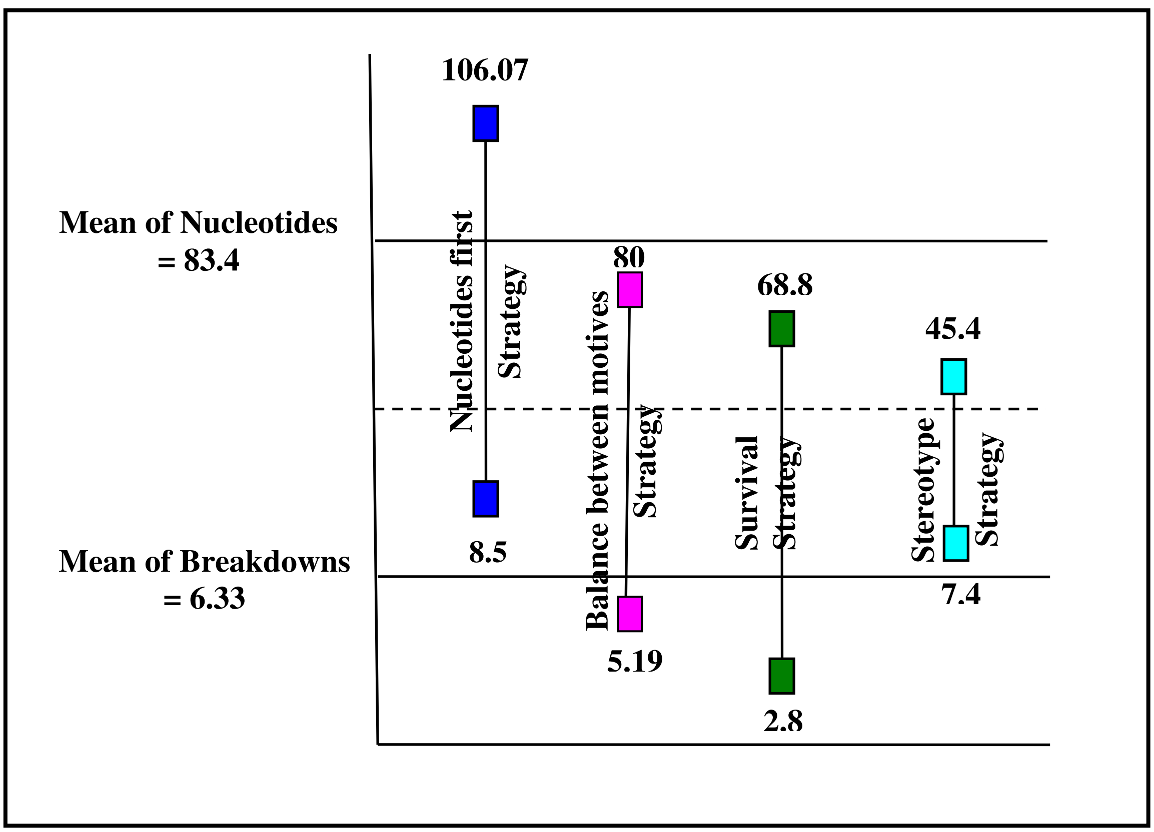


Figure 6.8: A comparison between the four different strategies–the whole sample (n=40).

6.2 Simulating Different Action Strategies and Two Single Cases

6.2.1 Introduction:

In this section, we are going to explain how we simulated the different human action strategies by the PSI-agent. We simulated the different participants' strategies by varying the PSI-parameters. Figure 6.10 (see below) shows a screenshot with the PSI-parameters. As shown in figure 6.9 (see below), the PSI-agent is the same robot without the control of a human subject, but with the PSI-theory implementation serving as the robot's "soul". The PSI-agent reacts to its environment by forming memories, expectations, immediate evaluations, and possesses a number of fixed but individually different parameters which influence their behaviour and perception. These parameters of modulation determine the way of "operating" an intention. The PSI-agent operated with different parameters to simulate the respective strategies which the participants of group-A (15 females and 5 males – participants' age range was between 18 and 30 "M= 23.05, SD=4.22") used when playing the island game. The simulation time was varied, because we discovered that the participants had different playing-speeds when playing the island-game. While the participants with a fast playing-speed were given a long simulation time, those with a slower playing-speed were given a shorter simulation time.

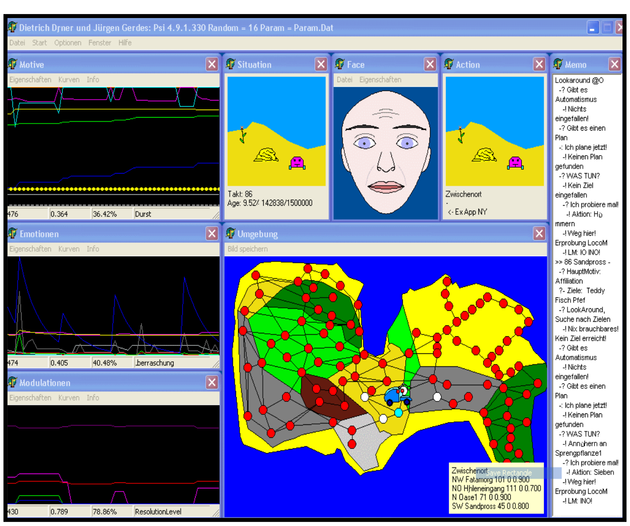


Figure 6.9: A screenshot with the PSI-Program (PSI plays island game).

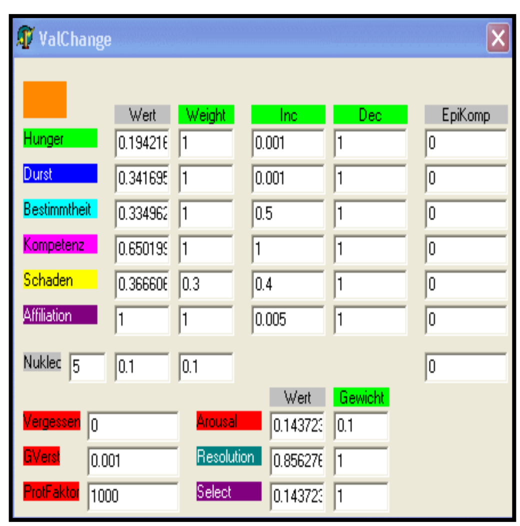


Figure 6.10: A screenshot with the PSI-parameters.

6.2.2 Simulating the nucleotides-first-strategy:

To investigate the ability of the PSI-model to simulate the strategies of single persons, the PSI-agent operated with the set of parameters (A) as shown in table 6.5 (p. 213) to simulate the participants (n=6)[*] who used the nucleotides-first-strategy when playing the game. Because their main motive was the task motive (i.e., collection the nucleotides), a high value was given to the weight of the task motive in this set of parameters. The set of parameters (A) was operated with a simulation time of 1.500.000 cycles. Twenty different profiles were produced by the PSI-agent for these parameters. Table 6.7 (p. 213) shows the results of the set of parameters (A) and figure 6.11 (p. 214) shows the mean of results of the twenty different profiles which were produced by the PSI-agent for the set of parameters (A) and the mean of the participants' results for those who used the nucleotides-first-strategy.

As mentioned in section 6.2.1(p.209), the participants had different playing-speeds when playing the island-game. Therefore, the PSI-agent operated with the set of parameters (B) as shown in table 6.6 (p. 213) with a simulation time of 1.600.000 cycles to simulate the different playing-speeds for those who used the nucleotides-first-strategy. Twenty different profiles were produced by the PSI-agent for these parameters. Additionally, the values of increment and decrement of hunger and thirst motives got lower values in the set of parameters (B) than in the set of parameters (A). The reason for this modification was to simulate the slight differences between the participants' personalities, although they used the same strategy (i.e., the nucleotides-first-strategy). Table 6.8 (p. 213) shows the results for the set of parameters (B) and figure 6.12 (p. 214) shows the mean of results of the twenty different profiles which were produced by the PSI-agent for the set of parameters (B) and the mean of the participants' results for those who used the nucleotides-first-strategy.

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[*] Six participants from group-A used the nucleotides-first-strategy as shown in table 6.2, p. 205.

6.2.3 Simulating the survival-strategy:

To investigate the ability of the PSI-model to simulate another different strategy, the PSI-agent operated with the set of parameters (C) as shown in table 6.9 (p. 215) to simulate the participants (n=4)* who used the survival-strategy when playing the game. Because their main motive was to protect the robot from breakdown by looking for the objects which could satisfy the existential needs of the robot, high values were given to the weights of the existential needs. Additionally, the weights of the existential needs were higher than the weight of the task motive. The set of parameters (C) as shown in table 6.9 (p. 215) was operated with a simulation time of 2.000.000 cycles. Twenty different profiles were produced by the PSI-agent for these parameters. Table 6.10 (p. 215) shows the results for the set of parameters (C). Figure 6.13 (p. 215) shows the mean of the twenty different profiles which were produced by the PSI-agent for the set of parameters (C) and the mean of the participants' results for those who used the survival-strategy.

6.2.4 Simulating the balance-between-motives-strategy (single case one):

To investigate the ability of the PSI-model to simulate single cases, we simulated the participant-xxviii's strategy as an example of those who used the balance-between-motives-strategy when playing the island game. The PSI-agent operated with the set of parameters (X) as shown in table 6.11 (p. 216) to simulate the participant-xxviii's strategy. Because the participant-xxviii considered the robot's needs and the task motive (i.e., collecting the nucleotides), the weight of selection threshold in this set of parameters got a moderate value. The set of parameters was operated once with a simulation time of 1.500.000 cycles. One profile was produced by the PSI-agent for this set of parameters to simulate the participant's strategy. Figure 6.14 (p. 216) shows results for this set of parameters and the results of the participant's strategy in the game.

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* Four participants from group-A used the survival-strategy as shown in table 6.2, p. 205.

6.2.5 Simulating the stereotype-strategy (single case two):

To investigate the ability of the PSI-model to simulate another different single case, PSI-agent operated with the set of parameters (Y) as shown in table 6.12 (p. 217) to simulate participant-xxxviii's strategy as an example of those who used the stereotype-strategy when playing the island game. Additionally, since the participant-xxxviii played the non-renewable resources version of the island game, we simulated the participant's strategy to investigate also the ability of the PSI-model to simulate single cases in different environments. Because participant-xxxviii had a high level of uncertainty, the weight of uncertainty motive got the highest value. The weight of the resolution level and the weight of the selection threshold got very low values in this set of parameters. The reason for this parameter setting was that the participant-xxxviii quickly changed her goals (e.g., the existential goals and the task goals "nucleotides") and she did not notice the differences between goals. The set of parameters was operated once with a simulation time of 500.000 cycles. One profile was produced by the PSI-agent for this set of parameters to simulate the participant's strategy. Figure 6.15 (p. 217) shows results for this set of parameters and the results of the participant's strategy in the game.

6.2.6 Simulating different action strategies of different personalities:

We used twenty different sets of parameters – parameters-D – as shown in table 6.13 (p. 218) to simulate twenty different human action strategies of the participants of group-(A). The participants of group-(A) used four different strategies (see table 6.2, p. 203). Therefore, different motives priorities, different selection thresholds, different resolution levels…..etc. were given to simulate the twenty different action strategies of the participants. Table 6.14 (p. 218) shows results for the sets of parameters (D) and figure 6.16 (p. 219) illustrates these results.

	Hunger	Thirst	Nucleotides	Damage avoidance	Uncertainty	Incompetence
Weight	1	1	1	0.3	0.1	0.001
Increment	0.009	0.009	1	0.4	0.1	0.001
Decrement	1	1	0	1	0.5	1
	Affiliation	Arousal	Resolution level	Selection threshold		
Weight	1	0.1	0.0	1	Forgetting	0.0
Increment	0.005	0	0	0	Protocol factor	1000
Decrement	1	0.1	0.5	1	Basic reinforcement strength	0.001

Table 6.5: Simulating the nucleotides-first-strategy — the set of parameters (A).

	Hunger	Thirst	Nucleotides	Damage avoidance	Uncertainty	Incompetence
Weight	1	1	1	0.3	0.1	0.001
Increment	0.001	0.001	1	0.4	0.1	0.001
Decrement	1	1	0	1	0.5	1
	Affiliation	Arousal	Resolution level	Selection threshold		
Weight	1	0.1	0.0	1	Forgetting	0.0
Increment	0.005	0	0	0	Protocol factor	1000
Decrement	1	0.1	0.5	1	Basic reinforcement strength	0.001

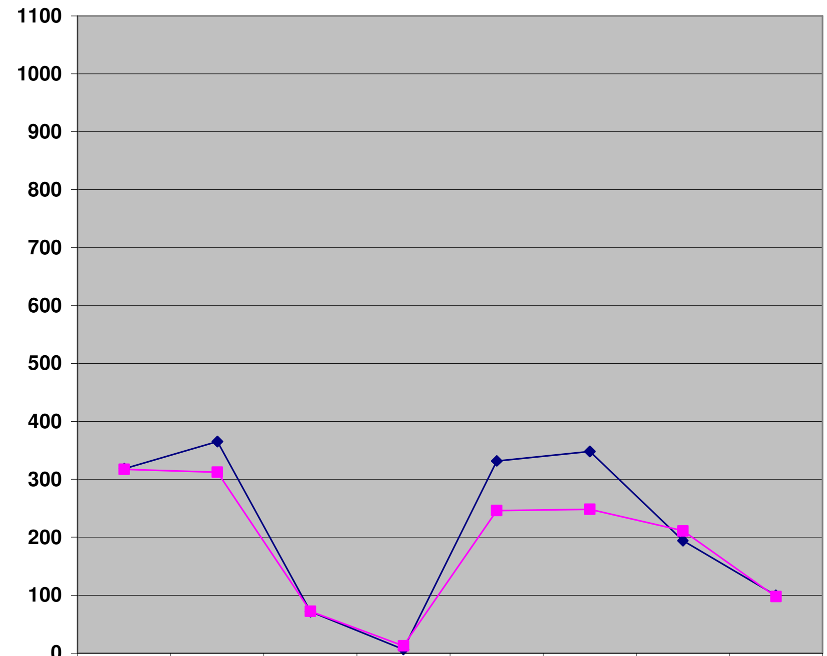
Table 6.6: Simulating the nucleotides-first-strategy — the set of parameters (B).

	NSL	NUL	NLOC	NEX	NAGG	NSM	NUM	NNUK
Mean	317,4	312,25	72,15	12,65	245,8	248,45	210,85	97,45
SD	25,2	35,12	13,71	0,49	11,24	22,98	24,01	14,38

Table 6.7: Results for the set of parameters (A).

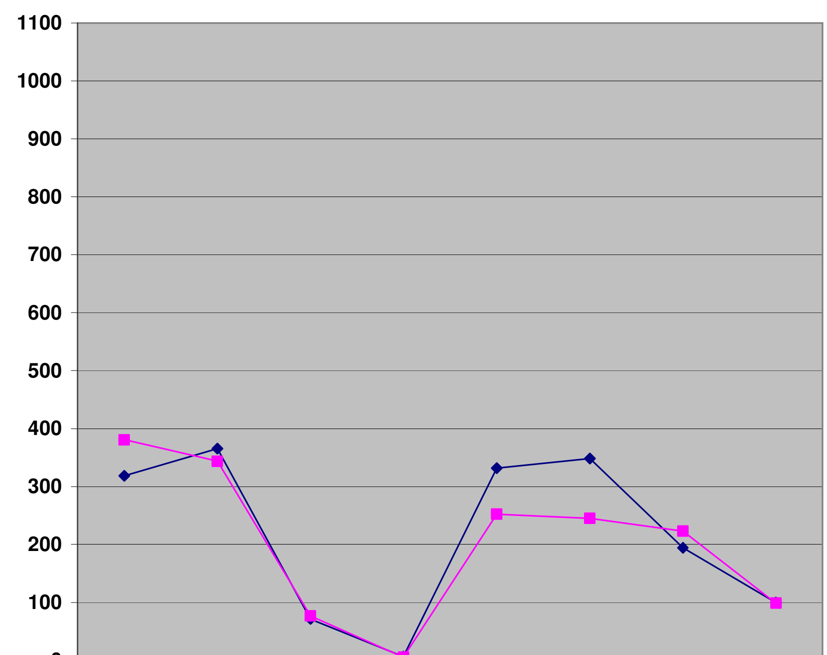
	NSL	NUL	NLOC	NEX	NAGG	NSM	NUM	NNUK
Mean	380,75	343,7	76,7	5,2	252,25	245,3	222,65	98,9
SD	35,15	43,16	12,61	0,62	14,39	19,25	31,58	10,87

Table 6.8: Results for the set of parameters (B).



	NSL	NUL	NLOC	NEX	NAGG	NSM	NUM	NNUk
Nucleotides first-strategy (group-A)	318.33	365.33	71.33	6.17	331.67	348.17	194.17	100
PSI-parameter-(A)	317.4	312.25	72.15	12.65	245.8	248.45	210.85	97.45

Figure 6.11:
Mean of the results for the set of parameters (A) and the mean of the participants' results of those who used the nucleotides-first-strategy (n=6).



	NSL	NUL	NLOC	NEX	NAGG	NSM	NUM	NNUk
Nucleotides first-strategy (group-A)	318.33	365.33	71.33	6.17	331.67	348.17	194.17	100
PSI-parameter-(B)	380.75	343.7	76.7	5.2	252.25	245.3	222.65	98.9

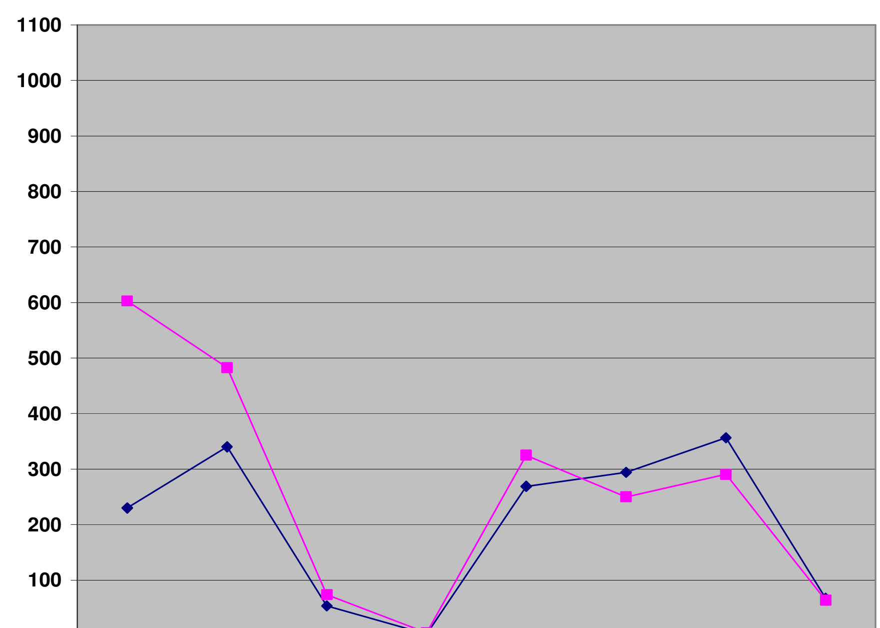
Figure 6.12:
Mean of the results for the set of parameters (B) and the mean of the participants' results of those who used the nucleotides-first-strategy (n=6).

	Hunger	Thirst	Nucleotides	Damage avoidance	Uncertainty	Incompetence
Weight	1	1	0.6	0.3	0.1	0.001
Increment	0.001	0.001	0.2	0.4	0.1	0.001
Decrement	1	1	0	1	0.5	1
	Affiliation	Arousal	Resolution level	Selection threshold		
Weight	1	0.1	0.0	1	Forgetting	0.0
Increment	0.005	0	0	0	Protocol factor	1000
Decrement	1	0.1	0.5	1	Basic reinforcement Strength	0.001

Table 6.9:
Simulating the survival-strategy — the set of parameters (C).

	NSL	NUL	NLOC	NEX	NAGG	NSM	NUM	NNUK
Mean	602,85	482,75	74	4,85	325	249,95	290,65	63,8
SD	92,71	89,05	18,37	0,88	41,13	37,89	48,25	12,28

Table 6.10:
Results for the set of parameters (C).



	NSL	NUL	NLOC	NEX	NAGG	NSM	NUM	NNUk
Survival-strategy (group-A)	230	340	53.5	2.75	269	294	356.25	67.25
PSI-parameter-(C)	602.85	482.75	74	4.85	325	249.95	290.65	63.8

Figure 6.13: Mean of the results for the set of parameters (C) and the mean of the participants' results of those who used the survival-strategy (n=4).

	Hunger	Thirst	Nucleotide	Damage avoidance	Uncertainty	Incompetence
Weight	1	1	0.7	0.1	0.5	0.5
Increment	0.0005	0.0005	0.3	1	0.01	0.01
Decrement	1	1	0.1	1	0.01	0.03
	Affiliation	Arousal	Resolution level	Selection threshold		
Weight	0.5	0.5	0.9	0.5	Forgetting	0.0
Increment	0.000005	0	0	0	Protocol factor	1000
Decrement	1	1	1	1	Basic reinforcement strength	0.001

Table 6.11:
The set of parameters (X) that was used to simulate the participant-xxviii's strategy. Participant-xxviii was considered as an example of those who used the balance-between-motives-strategy when playing the island-game.

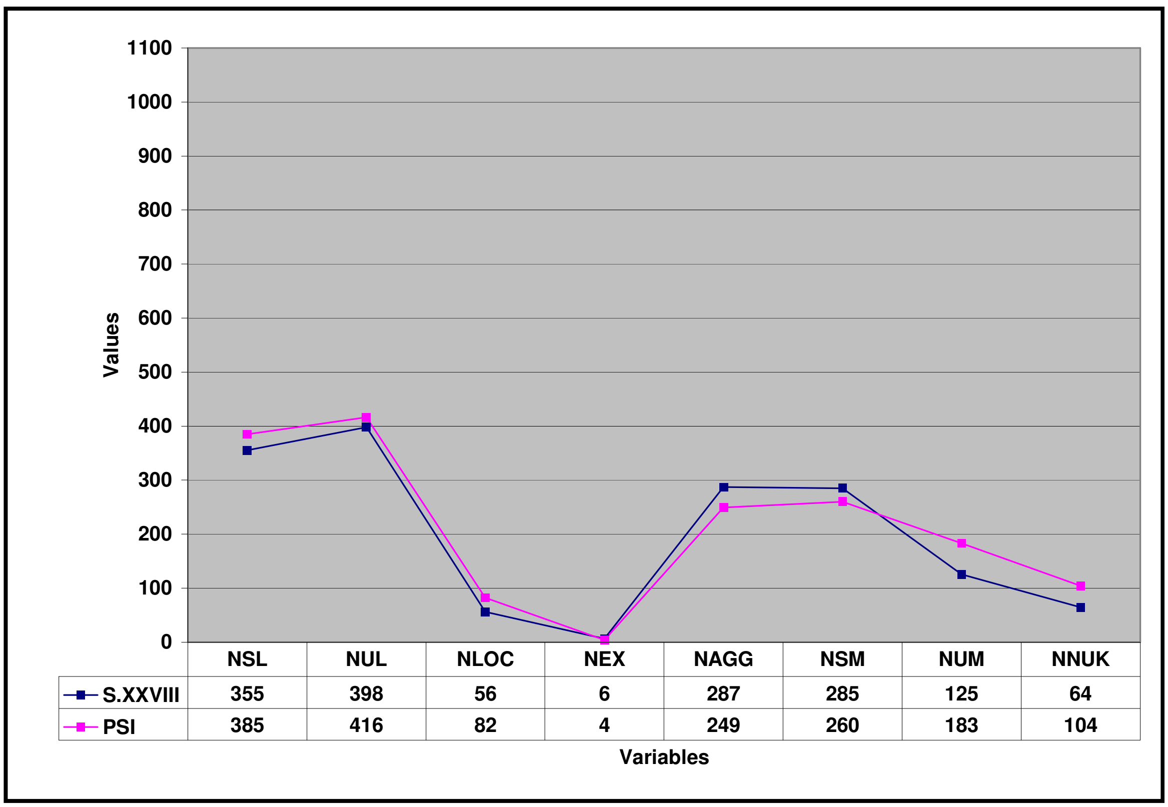


Figure 6.14:
Results of the participant-xxviii's strategy and the results for the set of parameters (X) that was used to simulate the participant's strategy. (An example of the balance-between-motives-strategy)

	Hunger	Thirst	Nucleotide	Damage avoidance	Uncertainty	Incompetence
Weight	1	1	0.7	0.1	0.5	0.5
Increment	0.0005	0.0005	0.3	1	0.01	0.01
Decrement	1	1	0.1	1	0.01	0.03
	Affiliation	Arousal	Resolution level	Selection threshold		
Weight	0.5	0.5	0.9	0.5	Forgetting	0.0
Increment	0.000005	0	0	0	Protocol factor	1000
Decrement	1	1	1	1	Basic reinforcement strength	0.001

Table 6.12:
The set of parameters (Y) that was used to simulate the participant-xxxviii's strategy. Participant-xxxviii was considered as an example of those who used the stereotype-strategy when playing the island-game.

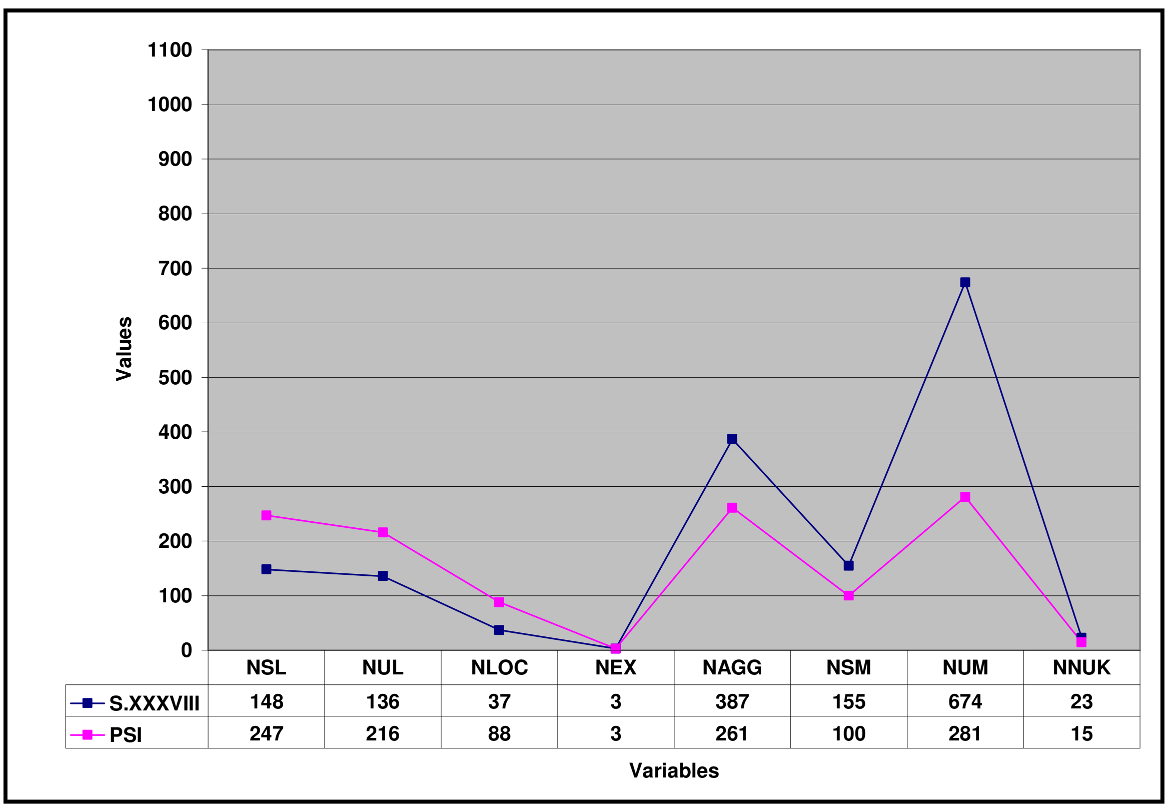


Figure 6.15:
Results of the participant-xxxviii's strategy and the results for the set of parameters (Y) that was used to simulate the participant's strategy. (An example of the stereotype-strategy)

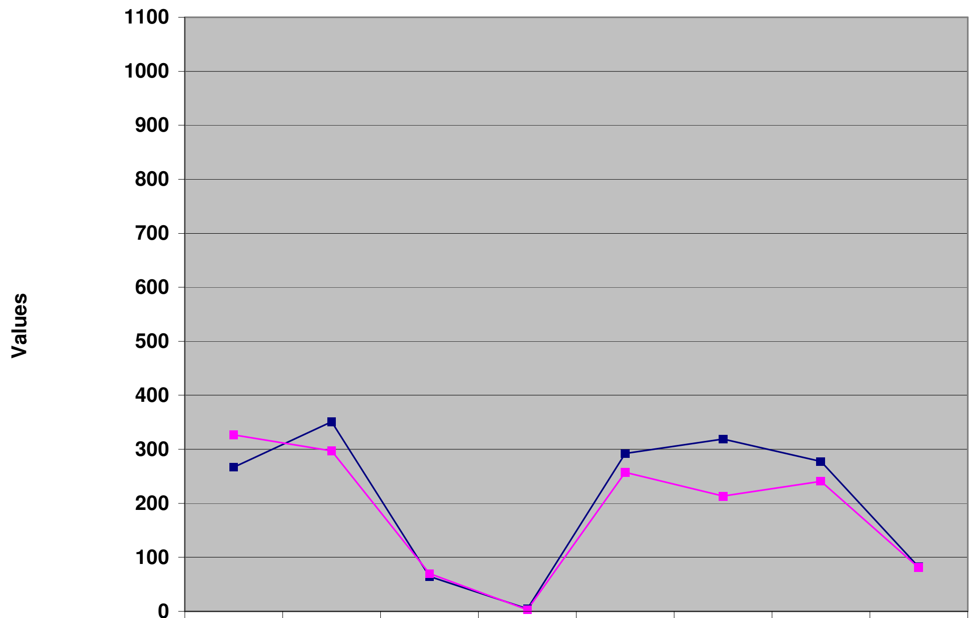
	Weight Hunger	Weight Thirst	Weight Nucleotide	Increment Nucleotide	Decrement Nucleotide	Weight Damage avoidance	Weight Certainty	Increment Certainty	Weight Competence	Increment Competence	Weight Affiliation	Arousal	Resolution Level	Selected Threshold
1	1	1	0.5	0.4	0.1	1	0.5	0.01	0.5	0.01	0.5	0.5	0.7	0.5
2	1	1	0.7	0.3	0.1	0.1	0.5	0.01	0.5	0.01	0.5	0.5	0.9	0.5
3	1	1	0.7	0.3	0.1	0.1	0.5	0.01	0.8	0.01	0.5	0.2	0.9	0.5
4	1	1	0.7	0.3	0.1	0.1	0.5	0.01	0.5	0.01	0.5	0.75	0.4	0.3
5	1	1	0.9	0.3	0.1	0.1	0.5	0.01	0.5	0.02	0.5	0.7	0.6	0.5
6	1	1	0.9	0.3	0.1	1	0.7	0.01	0.5	0.02	0.5	0.4	0.6	0.7
7	1	1	0.7	0.3	0.1	0.5	0.5	0.01	0.5	0.01	0.5	0.5	0.2	0.9
8	0.5	0.5	0.4	0.3	0.1	0.6	0.7	0.01	0.3	0.01	0.6	0.6	0.5	0.6
9	1	1	0.7	0.3	0.1	0.1	0.6	0.01	0.4	0.01	0.6	0.6	0.2	0.3
10	1	1	0.7	0.3	0.1	0.1	0.5	0.01	0.7	0.07	0.5	0.5	0.6	0.5
11	1	1	0.7	0.3	0.1	0.1	0.5	0.01	0.8	0.01	0.5	0.8	0.7	0.3
12	1	1	0.4	0.1	0.1	0.33	1	0.01	1	0.01	1	0.1	0.1	0.1
13	1	1	1	0.1	0.1	0.33	0.5	1	1	0.01	0.5	0.9	0.1	0.1
14	0.5	0.5	1	0.1	0.1	0.33	0.5	1	0.4	0.01	0.5	0.6	0.4	0.4
15	1	1	0.7	0.1	0.1	0.33	1	0.001	1	0.001	1	0.75	0.9	0.2
16	0.5	0.5	0.9	0.3	0.1	0.1	0.5	1	0.5	0.02	0.5	0.3	0.8	0.5
17	1	1	0.7	0.1	0.1	0.33	1	0.001	1	0.0001	1	0.75	0.9	0.8
18	0.5	0.5	0.4	0.3	0.3	0.1	0.5	0.01	0.7	0.07	0.5	0.5	0.8	0.5
19	1	1	0.7	0.3	0.1	0.1	1	0.01	0.8	0.01	0.5	0.5	0.7	0.3
20	1	1	0.7	0.3	0.1	0.1	0.5	0.01	0.5	0.01	0.5	0.5	0.9	0.5

Increment Hunger (0.0005), decrement Hunger (1), Increment Thirst (0.0005), decrement Thirst (1), Forgetting (0), Protocol-Factor (1000), Basic Reinforcement Strength (0,001), Increment Affiliation (0,000005), Decrement Affiliation (1).

Table 6.13:
The sets of parameters (D) consist of twenty different sets of parameters those were used to simulate the twenty different profiles of personality.

	NSL	NUL	NLOC	NEX	NAGG	NSM	NUM	NNUK
Mean	**327**	**297,45**	**70,25**	**2,85**	**257,7**	**213,35**	**240,65**	**81,15**
SD	**100,11**	**101,55**	**15,78**	**0,99**	**28,34**	**37,53**	**45,26**	**21,74**

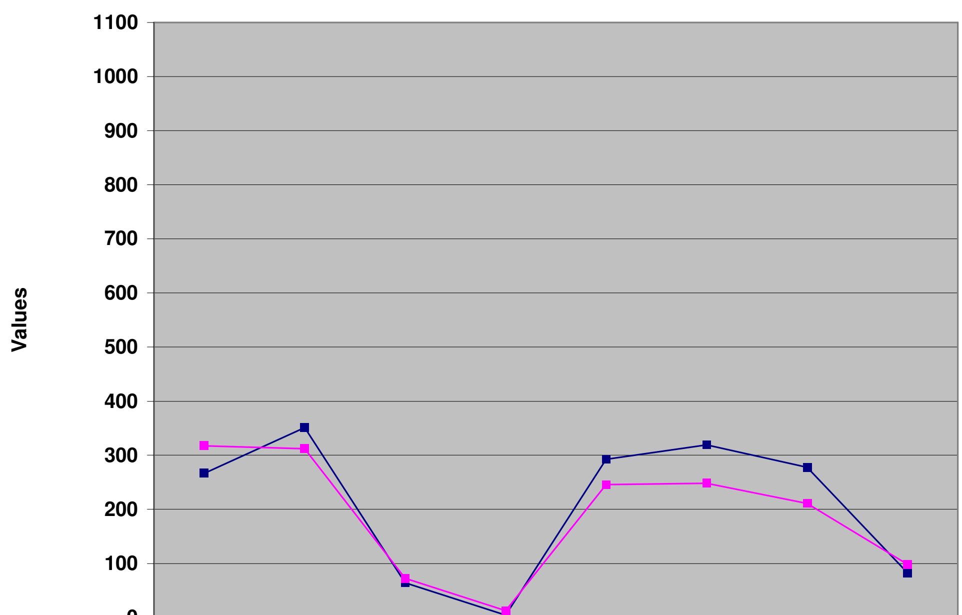
Table 6.14:
Results for the sets of parameters (D) those were used to simulate the twenty different profiles of personality.



	1	2	3	4	5	6	7	8
Mean (group"A") n=20	266.85	351.05	64.45	4.45	292.4	319.15	277.45	81.95
PSI-Parameters (D) n=20	327	297.45	70.25	2.85	257.7	213.35	240.65	81.15

Variables

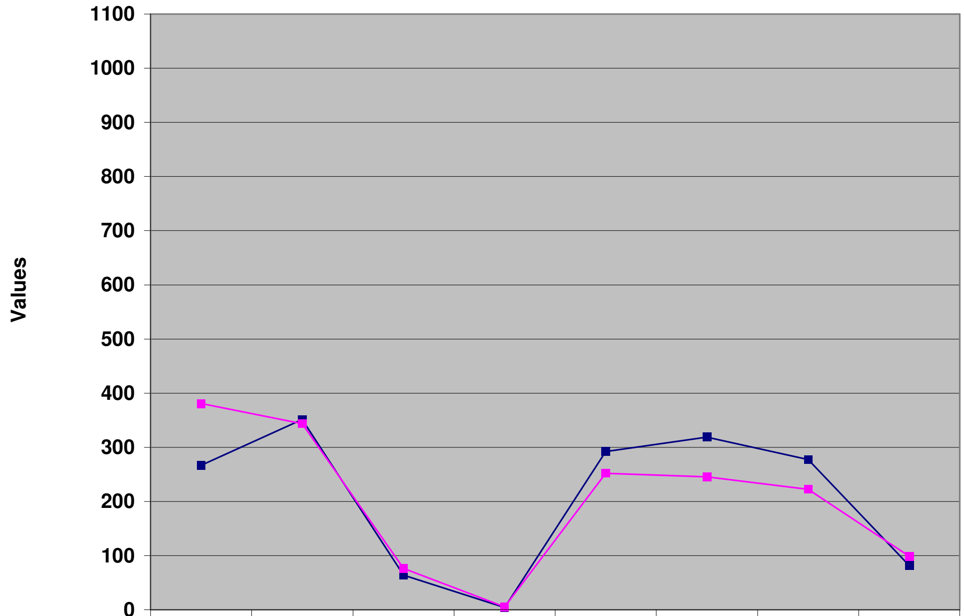
Figure 6.16:
Mean of the twenty different profiles of personality (the participants of group-A) and the mean of results for the twenty different sets of parameters (D).



	NSL	NUL	NLOC	NEX	NAGG	NSM	NUM	NNUK
Mean (group"A") n=20	266.85	351.05	64.45	4.45	292.4	319.15	277.45	81.95
PSI-Parameter (A)	317.4	312.25	72.15	12.65	245.8	248.45	210.85	97.45

Variables

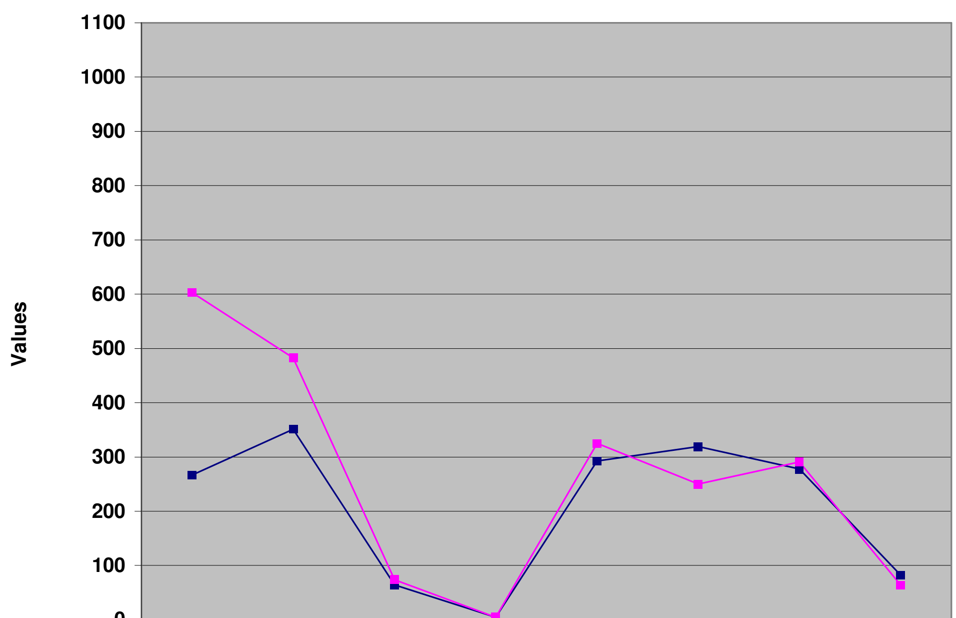
Figure 6.17:
Mean of the twenty different profiles of personality (the participants of group-A) and the mean of results for the set of parameters (A).



	NSL	NUL	NLOC	NEX	NAGG	NSM	NUM	NNUK
Mean (group"A") n=20	266.85	351.05	64.45	4.45	292.4	319.15	277.45	81.95
PSI-Parameter (B)	380.75	343.7	76.7	5.2	252.25	245.3	222.65	98.9

Variables

Figure 6.18:
Mean of the twenty different profiles of personality (the participants of group-A) and the mean of results for the set of parameters (B).



	NSL	NUL	NLOC	NEX	NAGG	NSM	NUM	NNUK
Mean (group"A") n=20	266.85	351.05	64.45	4.45	292.4	319.15	277.45	81.95
PSI-Parameter (C)	602.85	482.75	74	4.85	325	249.95	290.65	63.8

Variables

Figure 6.19:
Mean of the twenty different profiles of personality (the participants of group-A) and the mean of results for the set of parameters (C).

6.3 Correlations between participants' strategies and the results of the PSI-parameters

6.3.1 Introduction:

In this study we assume that the PSI-agent (and of course the theory behind the agent) had similar motives, emotions and cognitive processes as the human participants. The "personality" of a PSI-subject is the profile of parameters of the emotional regulations; such parameters are for instance, the gradient of the increase of arousal (dependent on the increase of a need) or the gradient of the decrease of competence when inefficiency is noticed (see: Dörner & Starker, 2004). Therefore, we set the already mentioned sets of parameters in a way that could simulate and produce similar strategies which the participants used in the experiment. That means we gave the PSI-agent different "personalities".

6.3.2 Results of the correlations:

The results of the participants of group-A with respect to the eight dependent variables* were correlated with the results of the PSI-agent operating with the sets of parameters A, B, C and D. Table 6.15 shows correlations between the participants' results with the results for the sets of parameters A,B,C and D.

Correlations between the data of participants with the data of PSI-parameter-	Canonical Correlation
A	0.92
B	0.91
C	0.89
D	0.88

Table 6.15: Results of correlations between the results of the participants of group-A with the PSI-program executions of the four parameters (A, B, C and D).

* The eight dependent variables were defined in chapter five (5.1.8, p. 154).

6.4 General Discussion

In figures 6.11, 6.12 (p. 214) and 6.13 (p. 215), we see that the PSI-model produces strategies which are similar to those of the participants when playing the island-game. Figures 6.11and 6.12 (p. 214) show that the PSI-agent operating with the set of parameters (A) and the PSI-agent operating with the set of parameters (B) simulated the strategies of those who used the nucleotides-first-strategy (n=6). Figure 6.13 (p. 215) shows that the PSI-agent operating with the set of parameters (C) simulated the strategies of those who used the survival-strategy (n=4).

Two single cases were also simulated by the PSI-agent operating with the sets of parameters X and Y. The sets of parameters X and Y were adjusted in a way that could simulate the strategies of the two participants. We simulated each single case by one set of parameters as shown in table 6.11 (p. 216) and table 6.12 (p. 217). Figure 6.14 (p. 216) and figure 6.15 (p. 217) show the results of these simulations. The simulations of the two single cases indicated that the PSI-model is able to simulate different single case strategies. Additionally, the PSI-agent followed the similar order of motives which the two single cases used.

As shown in table 6.15 (p. 221), we correlated the results of the participants of group-A (n=20) with the results for the sets of parameters-A, B, C and D. The results of correlations (i.e., 0.92, 0.91, 0.89 and 0.88) indicate that there are highly significant correlations between the results of the PSI-agent operating with the sets of parameters A, B, C and D, and the results of the human strategies. As demonstrated in table 1.1 (chapter one, p.20), we argued that the PSI-agent can simulate most of the different action strategies which can be found with man and it is possible to generate patterns of emotional behaviour similar to the patterns of human behaviour by varying the PSI-parameters. As shown in table 6.15 (p. 221), the correlation (i.e. 0.88) between twenty different human strategies and the results for the twenty different sets of parameters which simulated these strategies is significant. This high correlation indicates that the PSI-model can simulate different action strategies which can be found with different personalities. Figure

6.16 (p. 219) illustrate these results (i.e., the mean of the twenty different profiles of personality (participants of group-A) and mean of the results for twenty different sets of parameters (D). The results are consistent with our hypotheses and our predictions that the PSI-model can simulate single cases and different strategies and personalities. On the applied perspective, the PSI-theory can help to predict the behaviour of participants in uncertain environments which contain different goals. The PSI-theory provides a way to analyse such action strategies and to simulate these strategies by the PSI-agent.

The results of the current experiment and simulation are consistent with the results of experiments from Dörner and his co-workers which checked the relation of the PSI-model to human behaviour (see: Detje & Künzel, 2003; Dörner, 1999; Dörner, 2000; Dörner, 2001; Dörner et al. ,2002; Dörner, & Hille, 1995; Dörner, & Schaub, 1998; Hille, 1998, Elkady, 2005; Hoyer, 2003; Künzel, 2004)). Different forms of complex, dynamic, maze-like environments were used, where human participants had to play a kind of adventure game. In general, the results of these experiments show that it is possible to predict human behaviour by the PSI-theory to a satisfactory degree (Dörner & Starker, 2004). Bartl & Dörner (1998) found that the behaviour of the PSI-model and human behaviour in the BioLab-game were remarkably parallel. Hoyer (2003) found that under pressure a participant panics and switches rapidly between different strategies, and that can be interpreted as an expression of a rapid decline in competence when confronted with complexity and uncertainty. Additionally, the behaviour of the PSI-model indicates that the integration of cognitive, emotional, and motivational processes of PSI-theory is sound and can be used to explain human behaviour in complex systems.

As mentioned in chapter three, the capabilities* of an architecture refer to what the architecture as a system is able to do. The main objective in this chapter was to exactly determine what has to be measured and which criteria might be taken into

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* For further details about the evaluation criteria of an agent see chapter three (3.4, p. 90).

account to evaluate and highlight the strong and weak aspects of the behaviour of the PSI-agent. We will evaluate the PSI-agent in corresponding to the major agent criteria as follows:

In general, a system is said to learn if it is capable of acquiring new knowledge from its environment. Learning may also enable the ability to perform new tasks without having to be redesigned or reprogrammed, especially when accompanied by generalization. The PSI-agent is supplemented with appropriate mechanisms which enable the system to learn and to explore the environment. One of these mechanisms is the "uncertainty motive". Therefore, the PSI-model is able to acquire knowledge especially when the PSI-model discovers a difference between internal expectations and external observation and when the PSI-model is operating in an uncertain environment. In addition, the PSI-agent, by such activities as; observing; thinking; and trial and error behaviour which produce certainty, learns the rules governing a certain domain of reality and learns the outcomes of its own actions. This will increase the number of certainty-signals and thus the "tank of certainty" will be refilled. And so the need for certainty disappears. The PSI-agent was programmed to perceive objects and places, generate plans, and execute action sequences by modifying existing nodes and/or by creating autonomously new nodes to remember a novel experience. Moreover, because the PSI-model stores events in its memory for future retrieval, the PSI-model could provide the means for self-modification of behaviour in future when the agent is challenged by un-familiar situation. In addition, the PSI-model can be refined by detecting and recovering from failures, specifically when a discrepancy appears between what was projected to occur and what actually occurred during action. PSI-agent shows the following forms of deliberative behaviour:

- Exploring the reality in order to add new information in memory (i.e., in case of a lack of certainty).
- Storing this knowledge for future retrieval when is needed (e.g., under a pressure of an urgent motive).
- Avoiding failures as possible and that is a result of learning from feedback.

- Connecting gaols with their motives successfully.
- Deciding which goals are needed in case of exposed to new location.
- Eliciting proper operators from memory in order to handle objects (or goals).
- Deciding autonomously which and when a motive should be satisfied.

Furthermore, the PSI-agent implements stimulus-response rules (i.e. object-operator actions) to explore unknown objects. These rules are always consulted when the agent must choose an action to perform (especially when uncertainty motive is high and the objects or stimuli in the current situation are new or unknown). If an operator applies to an object, the successful operator is stored with its object in the PSI-memory and in this way the PSI-memory will increase. In the PSI-agent, learning is not constrained to occur monotonically; rather to occur non-monotonically. When any new knowledge is gained through learning, the PSI-model is adding knowledge to the knowledge base which existed previously. Therefore, as the PSI' experiences increase, the sets of experiences and neural nodes are strengthened and the next classification of a similar experience will then be more certain and rapid. Since world knowledge is not explicit, knowledge in the PSI-model can be added by the agent itself because of the existence of uncertainty motive.

The PSI-agent uses analogy-tactic which is acquired from solving a previous problem in a domain. The analogy-tactic means here a comparison between two different things (e.g., objects or situations) which are alike in some respects in order to highlight some form of similarity (e.g., the two objects perform a similar function by a similar mechanism). Points of comparison may include parts of a whole or common attributes (e.g., trees). This tactic is evoked when the PSI-agent comes to a place where a new motive's satisfaction is similar to a previously satisfied one. The analogy-tactic then directs the PSI-agent in the direction that leads to the previous solution (i.e., satisfaction). That is because the PSI-agent develops a set of similarity between features of objects and then applies the solution (e.g., appropriate operators) from the known problem to the new problem.

In robotic agents, an agent is given instructions and information by a programmer about the environment, domain knowledge, or how to accomplish a particular task. Or a programmer simply gives the agent the knowledge in a sequential series of instructions. Such non-autonomous features of learning do not exist in the PSI-model. When the PSI-robot begins to manage the task, it works autonomously and does not need the guidance of the PSI's programmer.

With respect to generalization capability, in the PSI-model when a connection between stimulus and response (i.e., an object and its operator) is created, it is available for immediate application. What is learned, the PSI-agent transfers it over different instances of the same problem and this transfer is a direct result of the ability of generalization. Also, the PSI-agent is able to transfer and apply knowledge that was acquired to another domain in the same environment.

With respect to the taskability of an agent which refers to the ability of an agent to perform different tasks without having to be reprogrammed (see: Laird, 1991, p.12; Langley& Laird, 2002, p.19), the PSI-model has been used in a wide variety of task domains involving planning and problem solving such as island 2D game (versions I, II, and III) and island 3D (version I). The long-term goal of the PSI-model is to be as general as the human information-processing system which focuses on sensory-motive-motor tasks. The PSI-model can be applied to a variety of robot control problems for the purpose of exploring, analyzing and handling uncertain environments by using its independently planning mechanism and motivations. In addition, the PSI-model is most appropriate for uncertain environments where actions have uncertain outcomes, and simulation-time environments which involve multi-goals and different tasks. Based on the nature of the PSI-model, maintaining coherence in the light of multiple and simultaneous goals would seem to be an important issue in the PSI-model, since all interactive processes run parallel and the PSI-model applies perceptual filter (i.e. resolution level). And because a domain may require an agent to perform many different types of tasks simultaneously in order to survive, the PSI-model supports multiple, simultaneous goals.

As explained by Dörner* (1997, p. 18), the PSI-model can manipulate different and multiple tasks. For example, in such environment (i.e. the world of PSI)* there are different types of events in which the PSI-model should learn it (ibid). For example:

1. There are positive events, which indicate the possibility to satisfy one's needs. Such events are wells and petrol-stations.
2. There are negative events which may cause damages and pains to the robot. In the world of the PSI, roads in a bad state or rock-falls are such events.
3. There are helpful events. For instance, a thoroughfare, which opens suddenly, is shortening the distance to a certain goal
4. There are hindering events. For instance, barred roads, which make detours necessary.
5. Additionally there are indicators for all these events (i.e., signals), which indicate that a petrol station is closed.

In the beginning of the simulation, the PSI-model did not know anything about its environment and had to learn its characteristics. After a while, the PSI-model learned which roads should be avoided, which thoroughfares are open at which daytime. Additionally, the PSI-model learned the positions of the petrol stations and the wells and learned when these stations are open. The PSI-model learned also when the wells provide water and when not and the PSI-model learned which signs in the environment indicate blocked roads.

With respect to the reactivity of an agent (the ability of a system to respond to changes in an unpredictable environment), the PSI-agent has features of a reactive agent such as; perceiving its environment, interacting with it, and responding to changes which can occur on it. Moreover, the PSI-agent has memory to store what the robot has learned, to perform advanced control and to set expectations. Furthermore, the PSI-agent can exploit opportunities or avoid dangers as they arise. Also, the sensors of the PSI-agent are connected to perception unit and the

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* For further details about Dörner's research see section 4.4.2, p. 136.

PSI's memory. As new goals are learned, the PSI-robot is able to respond quickly to new circumstances or changes in the environment. The PSI-memory allows the robot to react to the changing situations in an uncertain environment effectively. When a sensor detects a change, it relays this information to PSI's memory to see if the input is appropriate for the current goal and the sub-goals. So, if the input is within the current goals, decision is taken immediately. If the input is not within the current goals, may be no action will be taken and the PSI-robot leaves the locomotion and searches the needed goals in a different place. This modulation of perception with respect to the current goals gives the PSI-model saliency in domains which require perception and coordinated action.

With respect to the efficiency and scaling of an agent, scaling in the PSI involves either the addition of new robotic capabilities or the application of existing capabilities in more complex ways. Therefore, additional robotic capabilities will be fully utilized and without further extension of the PSI-architecture.

6.5 Work in Progress

Introduction:

To investigate the best resolution levels which one should take into account when one tries to simulate human behaviour by the PSI-model. We have investigated the resolution level by operating one set of the PSI-parameters with different resolution levels systemically. Table 6.16 (see below) shows the PSI-parameter which was used to investigate the resolution level. Table 6.17 (see below) shows values of resolution levels which were investigated systemically. Figure 6.20 (p. 230) shows results of investigating different resolution levels. Table 6.18 (p. 230) shows suggested resolution levels and their results.

We excluded results which did fit in the results range of the participants with respect to the eight dependent variables (the eight dependent variables were defined in chapter five — 5.1.8, p. 154). Therefore, from our point of view, table 6.18 (p. 230) illustrated the best resolution levels which one should take into account when one tries to simulate human behaviour by the PSI-model.

	Hunger	Thirst	Nucleotide	Damage avoidance	Certainty	Competence
Weight	1	1	0.7	0.3	0.1	0.001
Increment	0.00009	0.00009	0.1	0.4	0.1	0.1
Decrement	1	1	0.5	1	0.5	1
	Affiliation	**Arousal**	**Res. Level**	**S. Threshold**		
Weight	1	0.1	0.0	0.1	**Forgetting**	0.0
Increment	0.00005	0	0	0	**P. Factor**	1000
Decrement	1	0.1	0.5	0.1	**B. R. Strength**	0.001

Table 6.16:
The set of parameters that was used to investigate the resolution level.

0.0 0 0.1	0.1 0 0.1	0.2 0 0.1	0.3 0 0.1	0.4 0 0.1	0.5 0 0.1	0.6 0 0.1	0.7 0 0.1	0.8 0 0.1	0.9 0 0.1	1 0 0.1
0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3
0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4
0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6
0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7
0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.8
0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9
1	1	1	1	1	1	1	1	1	1	1

Table 6.17:
Values of the resolution levels that were investigated systemically.

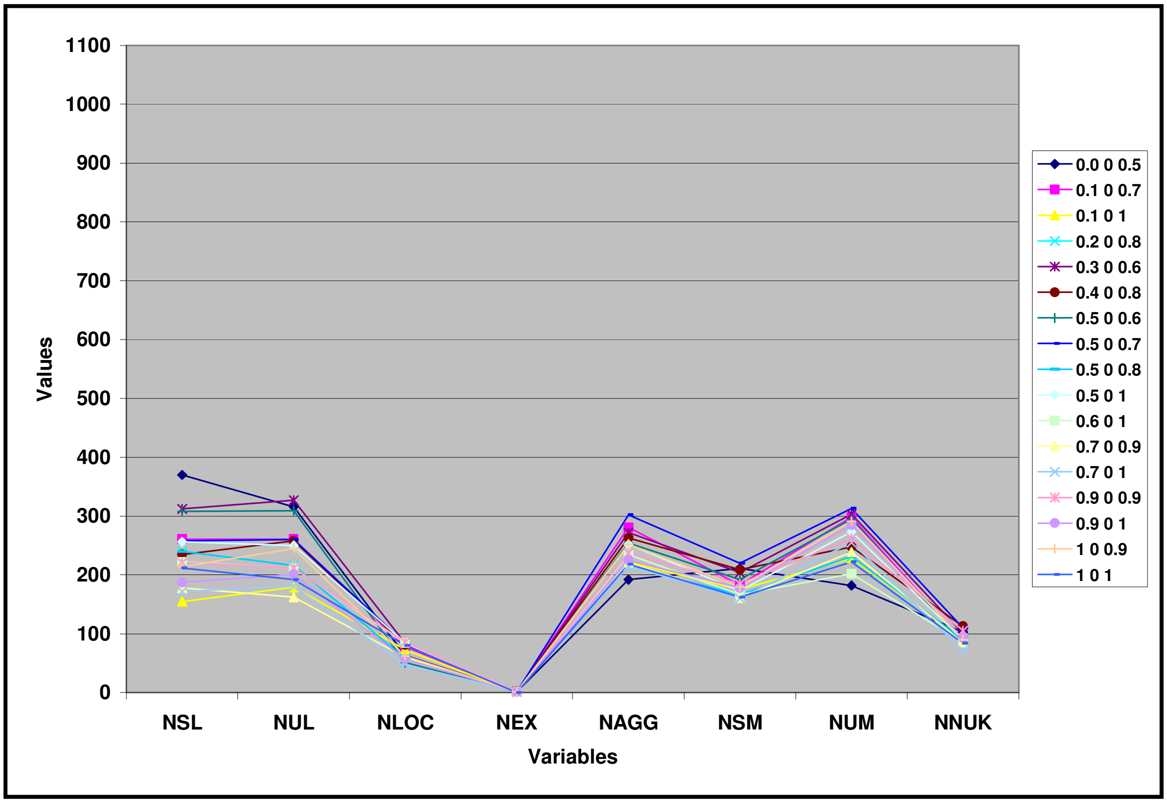

Figure 6.20:
Results of investigating different resolution levels.

R. Level	NSL	NUL	NLOC	NEX	NAGG	NSM	NUM	NNUK
0.0 0 0.5	370	316	63	1	192	211	182	103
0.1 0 0.7	261	261	78	1	281	183	298	88
0.1 0 1	155	179	73	0	222	175	228	91
0.2 0 0.8	240	216	58	1	215	167	231	90
0.3 0 0.6	312	327	84	2	272	204	303	101
0.4 0 0.8	235	258	81	2	263	209	248	113
0.5 0 0.6	308	309	51	1	254	192	295	85
0.5 0 0.7	258	260	84	1	302	220	313	110
0.5 0 0.8	240	216	58	1	215	167	231	90
0.5 0 1	256	250	85	2	252	173	273	90
0.6 0 1	222	212	84	1	235	167	202	86
0.7 0 0.9	178	162	60	1	221	161	239	85
0.7 0 1	172	181	48	1	215	160	255	72
0.9 0 0.9	221	212	86	1	237	185	262	105
0.9 0 1	187	201	57	1	225	178	285	93
1 0 0.9	214	245	62	1	252	180	291	90
1 0 1	212	192	80	0	218	162	222	84

Table 6.18:
Suggested resolution levels and their results.

Summary and Outlook

This dissertation has mainly attempted to investigate the ability of the PSI-model to simulate the interaction between emotions, motivations and cognition to explain different human action strategies and the action processes of single persons.

As shown in table 1.1 (see chapter one, p. 20), we suggested questions and hypotheses to investigate the ability of the PSI-model to simulate different human action strategies and the action processes of single cases. In the following section, I will discuss these questions and hypotheses with respect to the results of the dissertation:

- **What is the state of the PSI-agent's behaviour in corresponding to agent criteria?**

In respective of the agent criteria (the agent criteria were described in chapter three — 3.4, p. 90), we have investigated the behaviour of the PSI-agent and we have found that:

The PSI-agent is able to acquire knowledge from its environment independently. The PSI-agent can perceive objects, generate plans, and execute action sequences. The PSI-agent initially operates reflexively and then operates deliberatively.

In the PSI-model, learning is not constrained to occur monotonically; rather to occur non-monotonically. Based on the nature of the PSI-model, maintaining coherence, taskability, rationality, sociability and adaptation seem to be important issues in the PSI-model, since all interactive processes of the PSI-model run parallel. The PSI-agent is an autonomous agent which can operate on its own without the need for human guidance.

- **Can PSI-agent simulate all the different action strategies that can be found with man?**

As shown in this dissertation, the PSI-model can simulate the different strategies (e.g., the nucleotides-first-strategy, the balance-between-motives-strategy, the stereotype-strategy, and the survival-strategy) which had been used by the participants of the experiment when playing the island game. Correlations (i.e., 0.92, 0.91, 0.89 and 0.88) between the results of the twenty participants and the twenty different PSI-parameters which simulated the different participants' strategies were significant. Moreover, the PSI-agent seemed to exhibit the same motives, emotions and tactics as the human subjects.

- **It is possible to simulate the behaviour of individual human beings by the PSI-agent.**

Two action processes of two different personalities were investigated through the concepts of the PSI-theory to determine exactly which strategies had been used by these two different personalities and why they used these strategies when playing the island game. The analysis of these two different personalities indicated that one of them used the balance-between-motives-strategy because the participant had a moderate level of the selection threshold, while the other one had used the stereotype-strategy because this participant had a low level of the selection threshold, a low level of the resolution level and a low level of the basic reinforcement strength. Subsequently, we set the PSI-parameters to simulate these two strategies which had been used by these two different personalities. Results of the simulation showed that the PSI-agent could produce the same strategies which the two different participants had used when playing the island game. Moreover, qualitative analysis of the two single cases indicated that the PSI-model can also simulate single cases strategies. Additionally, the PSI-agent followed the same participants' motives, emotions, selection thresholds and resolution levels which the participants had used when playing the game. The results of the simulation were consistent with our hypotheses and our predictions that the PSI-model can simulate different human action strategies.

- **How can we improve the PSI-agent respectively to the theory behind the agent?**

Introduction:

Based on the observation and the qualitative analysis of the experiment, the following arguments are suggested to enhance the PSI-theory:

1. In the PSI-model, the competence-motive is dependent on the number of successes and failures and on the weights for the increment or decrement effects of successes or failures. If competence's weight has a high value, a high increase in competence will result, even with moderate success. If competence's weight has a low value, competence will not increase considerably even with great successes (see: Dörner, 2001). I observed that the increment and the decrement values on one's competence are not only affected by a success or a failure, but also they are affected by a state of a current urgent motive. When the pressure of an urgent motive is low, the increased competence after satisfying this motive is low too. And when the pressure of an urgent motive is high, the increased competence after satisfying this motive is high too. An urgent motive can be one or more of the existential motives, the affiliation motive, and the task motive (i.e. collecting the nucleotides). The increment and the decrement values on one's competence after an action follow different orders depending on a current urgent motive state as shown below in table 6.19 .

Participants	**A**	**B**	**C**	**D**
State of an urgent motive (e.g., the existential motives, the affiliation motive, and the task motive (i.e. collecting the nucleotides).)	20%	40%	70%	90%
Increased competence after satisfaction	Low	Medium	High	high

Table 6.19: Shows how the increase of one's competence after satisfaction depends on the state of the current urgent motive.

2. High levels of both uncertainty and incompetence motives reduce one's selection threshold. Therefore, it is easy for other motives to replace the current motive.

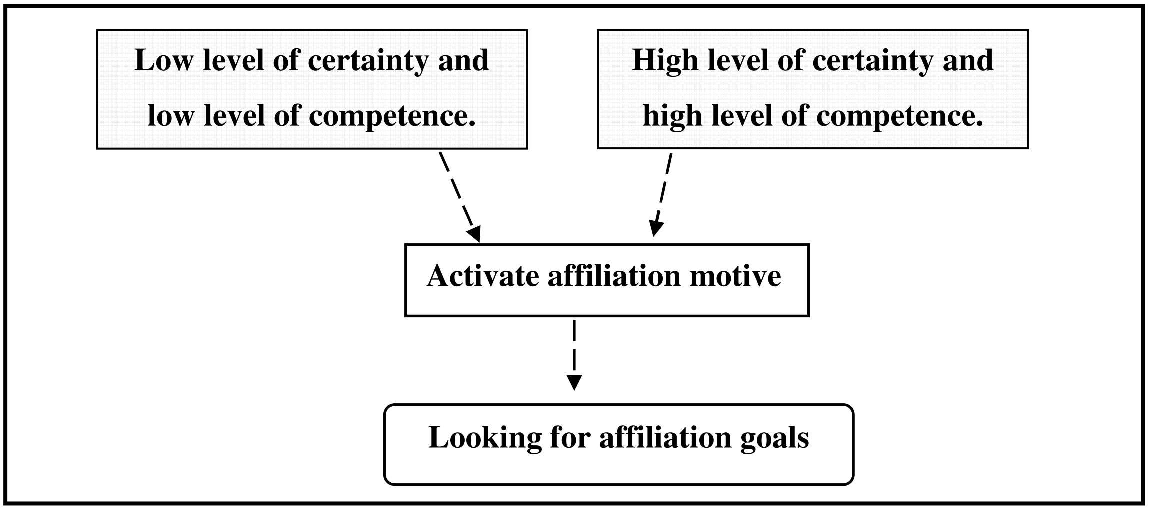

Figure 6.21: Affiliation motive is activated under specific circumstances.

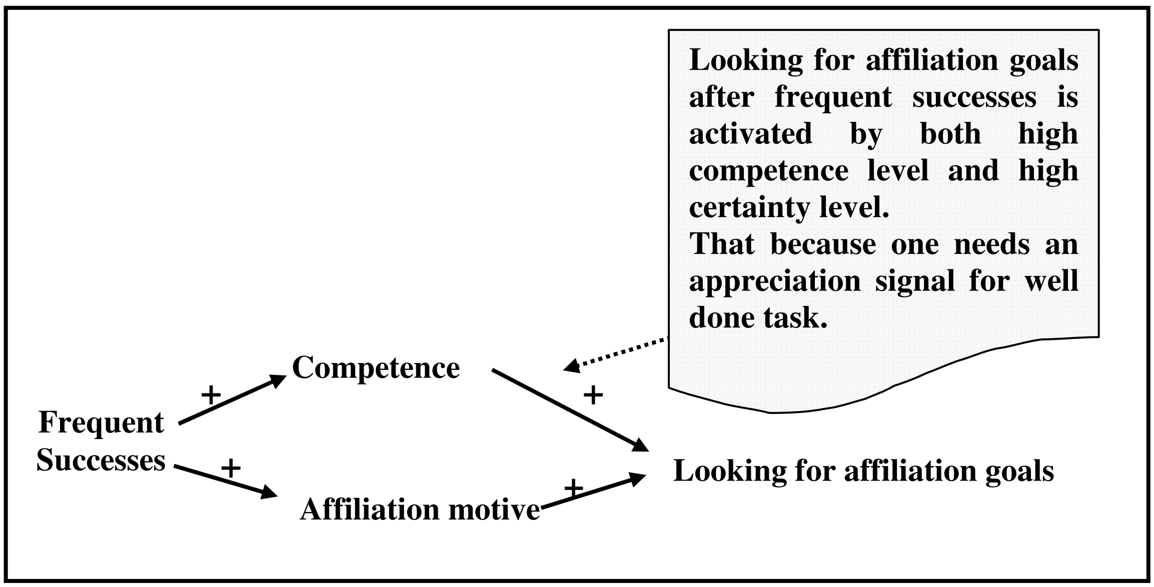

Figure 6.22: Looking for affiliation goals after frequent success.

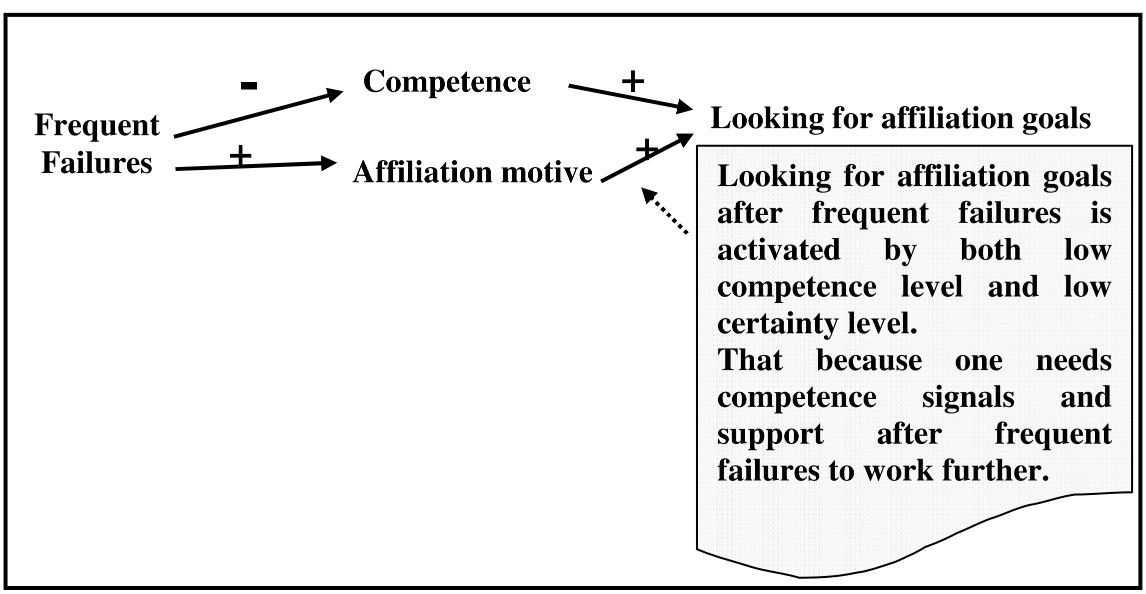

Figure 6.23: Looking for affiliation goals after frequent failures.

3. I observed that under the following circumstances the participants had satisfied affiliation motive:

I. After frequent successes: “success” here means that a participant is able to accomplish both tasks (i.e., collecting nucleotides and protecting the robot from breakdowns). Here, looking for affiliation goals after frequent success is activated by both high competence level and high certainty level. The reason for this is that one needs an appreciation signal for well done task after frequent successes.

II. After frequent failures: “failure” here means that a participant is not able to accomplish the task (i.e., collecting nucleotides or protecting the robot from breakdown) or a participant is not able to understand operators or objects or the geographical structure of the island. Here, looking for affiliation goals after frequent failures is activated by both low competence level and low certainty level. The reason for this is that one needs competence signals and support after frequent failures to work further.

When a participant’s competence is low and accompanied by low certainty, the affiliation motive is increased and/or activated. And when a participant’s competence is high and accompanied by high certainty, the affiliation motive is also increased and/or activated. Figures 6.21, 6.22 and 6.23 (p. 234) illustrate how affiliation motive is activated under these circumstances.

Additionally, at the beginning, when a participant has a high level of uncertainty; consequently, he has explored the surroundings and of course his competence was high after successful exploration process. In this case, affiliation motive was not activated, because the participant had considered that − increase of certainty and competence − as a minimum essential level of success to do both tasks well later.

In future work, the author will try to investigate the following question:

Why does a motive seem to be activated under special circumstances? (i.e., by other motives and at a certain time). The author’s hypothesis is that: “When two or more motives coincide at a certain time, another – third– motive is activated.” This work would be needed to improve the PSI-model of human action regulation.

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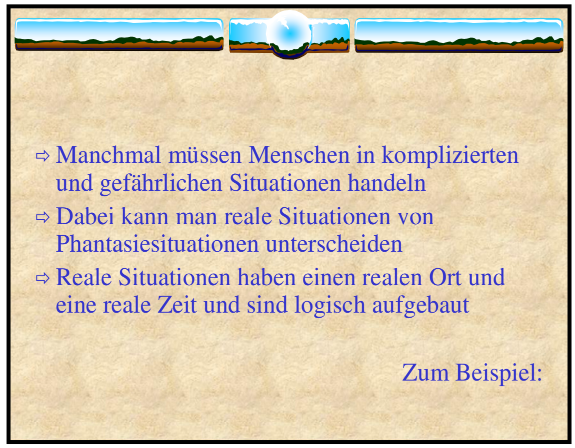
Appendix

The instructions of the island-game were presented by using the Power Point program. The original Power Point version that consisted of 62 slides was created and edited in English language by Ayman Elkady and translated to German language by Roman Seidl. In the following, a short version of this power point-24 slide- will be shown.


Willkommen beim
Institut für Theoretische
Psychologie

1


Manchmal müssen Menschen in komplizierten und gefährlichen Situationen handeln
Dabei kann man reale Situationen von Phantasiesituationen unterscheiden
Reale Situationen haben einen realen Ort und eine reale Zeit und sind logisch aufgebaut
Zum Beispiel:

2


Der Weltraum…

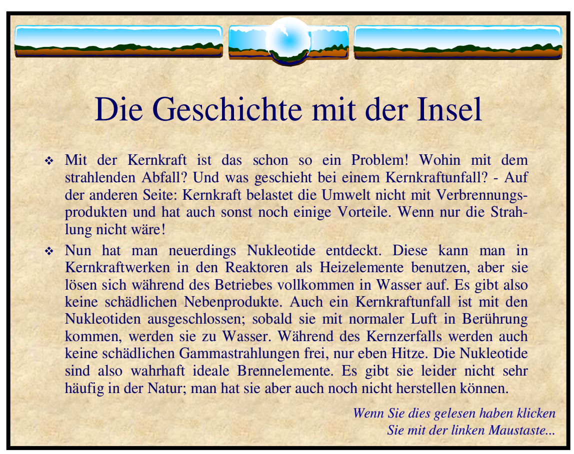
3


… oder die Natur

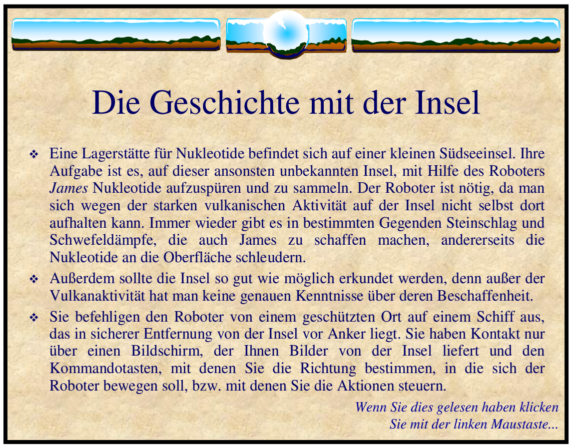
4


Phantasie-Situationen
Sie sind vielleicht nach einer anderen Logik aufgebaut.
Sie sind auch nicht an einen realen Raum oder eine bestimmte Zeit gebunden und es können andere Objekte als in der „wahren“ Realität möglich sein.

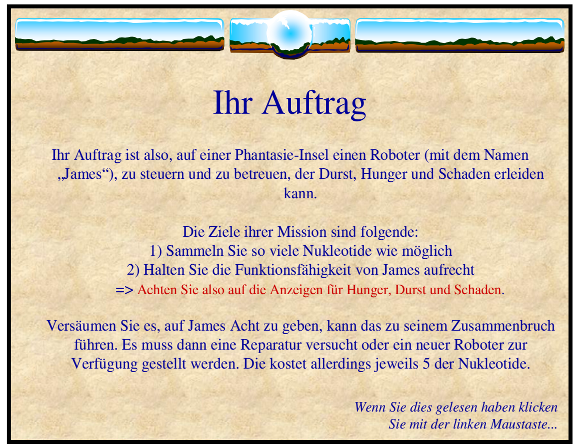
5


Die Geschichte mit der Insel
Mit der Kernkraft ist das schon so ein Problem! Wohin mit dem strahlenden Abfall? Und was geschieht bei einem Kernkraftunfall? - Auf der anderen Seite: Kernkraft belastet die Umwelt nicht mit Verbrennungsprodukten und hat auch sonst noch einige Vorteile. Wenn nur die Strahlung nicht wäre!
Nun hat man neuerdings Nukleotide entdeckt. Diese kann man in Kernkraftwerken in den Reaktoren als Heizelemente benutzen, aber sie lösen sich während des Betriebes vollkommen in Wasser auf. Es gibt also keine schädlichen Nebenprodukte. Auch ein Kernkraftunfall ist mit den Nukleotiden ausgeschlossen; sobald sie mit normaler Luft in Berührung kommen, werden sie zu Wasser. Während des Kernzerfalls werden auch keine schädlichen Gammastrahlungen frei, nur eben Hitze. Die Nukleotide sind also wahrhaft ideale Brennelemente. Es gibt sie leider nicht sehr häufig in der Natur; man hat sie aber auch noch nicht herstellen können.
Wenn Sie dies gelesen haben klicken Sie mit der linken Maustaste...

6


Die Geschichte mit der Insel
Eine Lagerstätte für Nukleotide befindet sich auf einer kleinen Südseeinsel. Ihre Aufgabe ist es, auf dieser ansonsten unbekannten Insel, mit Hilfe des Roboters *James* Nukleotide aufzuspüren und zu sammeln. Der Roboter ist nötig, da man sich wegen der starken vulkanischen Aktivität auf der Insel nicht selbst dort aufhalten kann. Immer wieder gibt es in bestimmten Gegenden Steinschlag und Schwefeldämpfe, die auch James zu schaffen machen, andererseits die Nukleotide an die Oberfläche schleudern.
Außerdem sollte die Insel so gut wie möglich erkundet werden, denn außer der Vulkanaktivität hat man keine genauen Kenntnisse über deren Beschaffenheit.
Sie befehligen den Roboter von einem geschützten Ort auf einem Schiff aus, das in sicherer Entfernung von der Insel vor Anker liegt. Sie haben Kontakt nur über einen Bildschirm, der Ihnen Bilder von der Insel liefert und den Kommandotasten, mit denen Sie die Richtung bestimmen, in die sich der Roboter bewegen soll, bzw. mit denen Sie die Aktionen steuern.
Wenn Sie dies gelesen haben klicken
Sie mit der linken Maustaste...

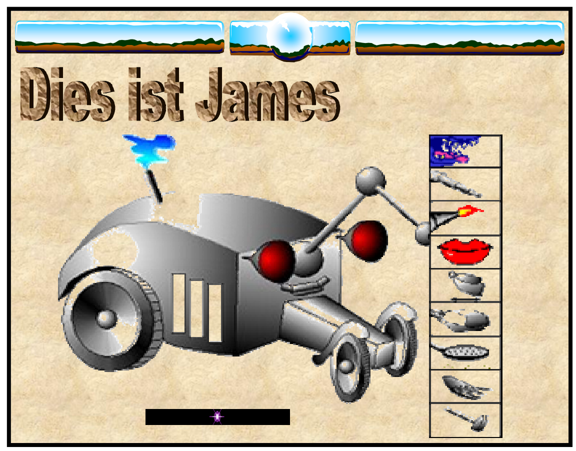
7


Ihr Auftrag
Ihr Auftrag ist also, auf einer Phantasie-Insel einen Roboter (mit dem Namen „James“), zu steuern und zu betreuen, der Durst, Hunger und Schaden erleiden kann.
Die Ziele ihrer Mission sind folgende:
1) Sammeln Sie so viele Nukleotide wie möglich
2) Halten Sie die Funktionsfähigkeit von James aufrecht
=> Achten Sie also auf die Anzeigen für Hunger, Durst und Schaden.
Versäumen Sie es, auf James Acht zu geben, kann das zu seinem Zusammenbruch führen. Es muss dann eine Reparatur versucht oder ein neuer Roboter zur Verfügung gestellt werden. Die kostet allerdings jeweils 5 der Nukleotide.
Wenn Sie dies gelesen haben klicken
Sie mit der linken Maustaste...

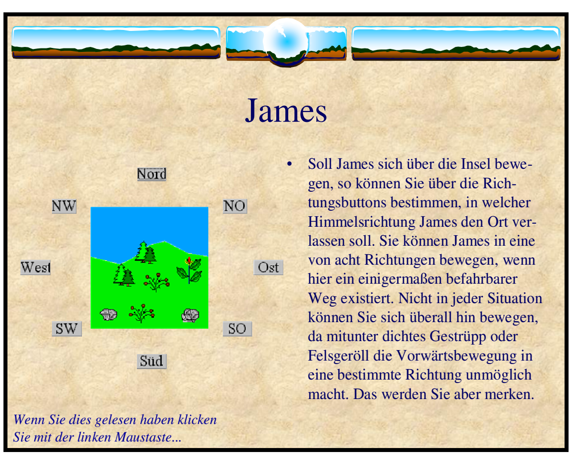
8


Wir erklären nun Einzelheiten
Schritt für Schritt…

9


Dies ist James

10

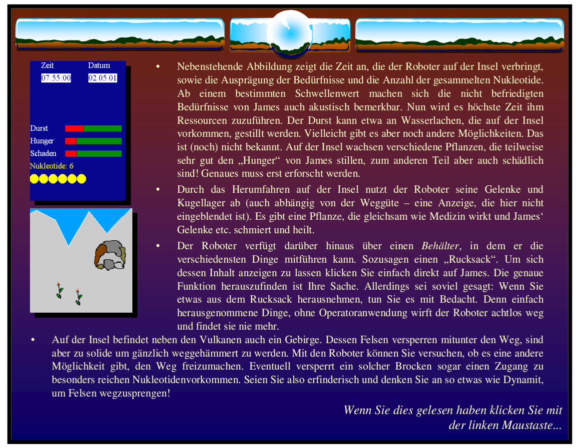

James
Nord
NW
NO
West
Ost
SW
SO
Süd
Soll James sich über die Insel bewegen, so können Sie über die Richtungsbuttons bestimmen, in welcher Himmelsrichtung James den Ort verlassen soll. Sie können James in eine von acht Richtungen bewegen, wenn hier ein einigermaßen befahrbarer Weg existiert. Nicht in jeder Situation können Sie sich überall hin bewegen, da mitunter dichtes Gestrüpp oder Felsgeröll die Vorwärtsbewegung in eine bestimmte Richtung unmöglich macht. Das werden Sie aber merken.
Wenn Sie dies gelesen haben klicken
Sie mit der linken Maustaste...

11


James
Auf Ihrem Monitor sehen Sie direkt in der Mitte eine Abbildung der Landschaft, wie sie sich James Kameraauge darbietet. Dabei handelt es sich oft um verschiedene Blickwinkel. Lassen Sie sich dadurch nicht verwirren. Auf dem kleinen Sichtfenster sehen Sie jeweils die Situation, in der sich James gerade befindet mit ihren verschiedenen Komponenten, wie Dünen, Höhlen, Pflanzen, Sträucher, Bäume usw.
Die Nukleotide sind kleine sechseckige bis runde Elemente, die Sie unschwer entdecken werden. Sie können sie dann jeweils einsammeln und mitnehmen. Manchmal aber sind die Nukleotide auch verborgen, und Sie müssen sie suchen. Dazu können Sie James umherfahren oder auch die in einer Situation vorfindbaren Objekte manipulieren lassen. Durch Mausklick können Sie einzelne Objekte (zum Beispiel einen Baum) auswählen, und James damit befehlen, sich diesem anzunähern. Anschließend können Sie James Operationen ausführen lassen. Dazu dienen die Werkzeuge an der rechten Leiste. James hat einen Greifarm, mit dem er Dinge aufnehmen kann. Dazu klicken Sie bitte den Greifarm von James mit der Maus an. Soll James anstelle des Greifens andere Operationen ausführen, so klicken Sie bitte die passenden Werkzeuge an. Unter dem Greifarm befindet sich beispielsweise ein Sieb, das bei Bedarf ausgefahren werden kann. Welche Operationen bei welchem Objekt sinnvoll sind und welche nicht, das werden Sie im Laufe des Versuchs selbst herausfinden.
Wenn Sie dies gelesen haben klicken
Sie mit der linken Maustaste...

12

13



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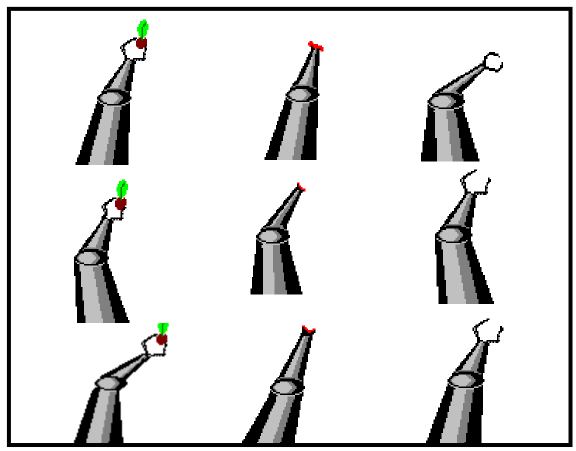

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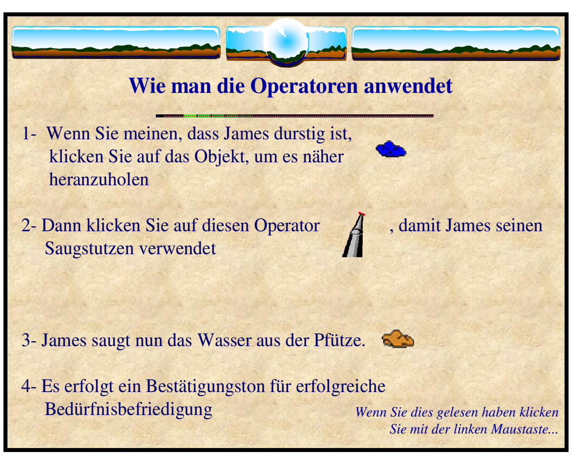

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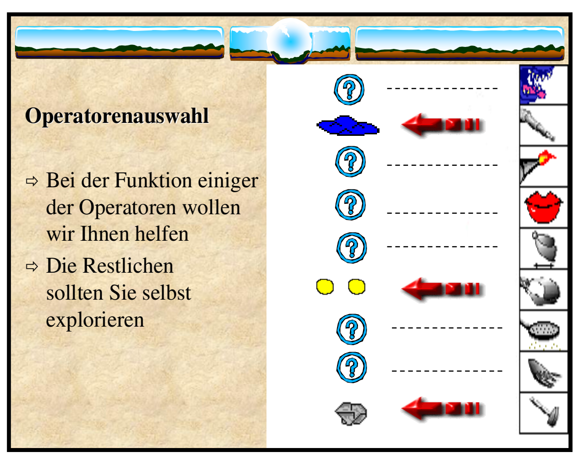

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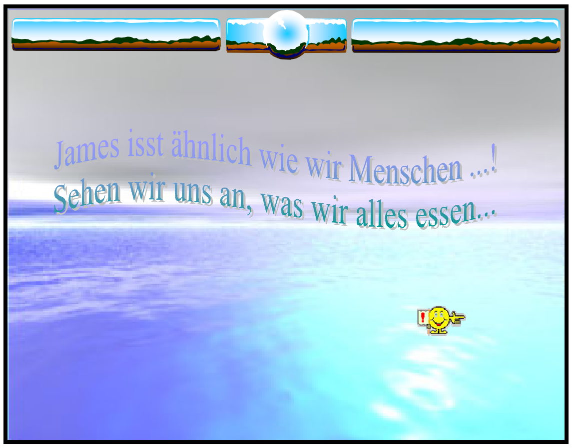

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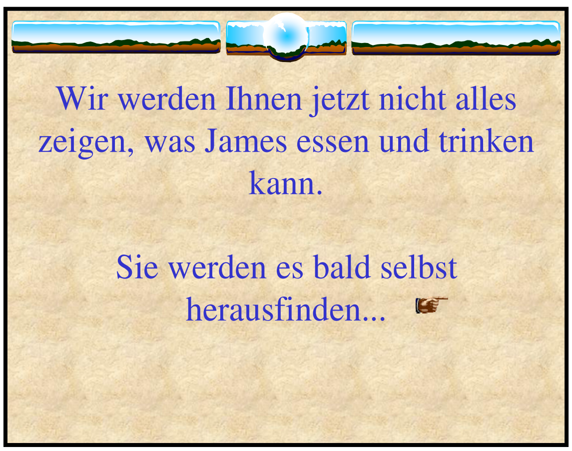

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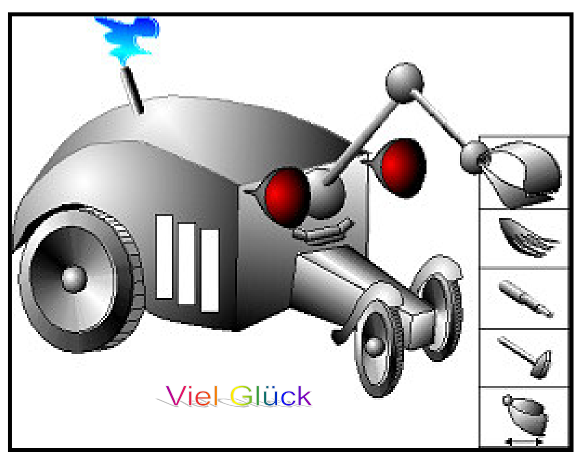

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