User-Centered Design of a Cognitive Control Unit for a Self-Optimizing Assembly System

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This work is dedicated to
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LIST OF CONTENTS

1 INTRODUCTION

1.1 Problem Statement

Cognitive engineering has become an important aspect of production systems research. To improve productivity, safety and well-being, it is important to highlight the role of human cognition in future production systems. Most conventional production systems are designed with their focus on advanced technology and a strong emphasis on automation. Design for cognitive compatibility plays a vital role in these complex work systems regarding the improvement of joint performance and optimization in human-machine and human-robot interactions.

Automated work systems are ubiquitously found in high-wage countries because these areas of the world feature both the high technological level and the abundance of financial capital necessary to design, develop and operate these systems. The development of automation in high-wage countries has helped producers to meet the needs of their customers in terms of quality and cost, which subsequently improves their respective competitive advantages. To remain competitive in high-wage countries, robots play a significant role because they provide an effective means of improving productivity, precision and throughput in automated work systems, as well as reducing the cost of automation (Acker, 2005).

The use of articulated robots has often been proposed for further improving productivity and reducing expenditure on personnel. However, advanced robotized production systems often require considerable financial investment, extensive configuration and high levels of maintenance, without directly adding value to the manufactured product (Klocke, 2009). Furthermore, there is a significant degree of difficulty in integrating advanced sensor and actuator technology into these work systems. A high level of robot usage generally requires complicated system integration, the standardization of interfaces and qualitatively elevated levels of process and material input (Acker, 2005). The higher the level of automation, the more complex it becomes to ensure the individual development of the knowledge, skills and abilities of the human operator. This represents a challenge for the establishment of a safe and efficient human-robot interaction (Schlick et al., 2009).

A solution is provided through the ergonomic design of human-robot interaction (HRI) and in developing self-optimizing work systems with balanced automation. This approach features a high level of robotic automation offering a broad range of advantages (in terms of precision, control and reproducibility), without hindering the human operator in utilizing and developing his or her individual knowledge, skills and abilities. Hence, ergonomic HRI presents the most advantageous option for maintaining productivity and increasing flexibility while continuously optimizing and adapting the corresponding manufacturing processes.

HRI is a comprehensive research area at the intersection of several academic disciplines such as psychology, cognitive science, artificial intelligence, computer science, robotics, engineering, and social sciences (Dautenhahn, 2007). HRI aims to improve human safety in work systems and enhance processes of continuous optimization, particularly in terms of cost reduction and increased efficiency. HRI research also focuses on studies regarding the design of a “linkage system” between humans and robots. How humans and robots interact and communicate is an important field of HRI research, but to transform and redesign tasks in a joint cognitive system with both human and robotic participants, it is especially useful to focus on both sides of this mutual interaction (Kim et al., 2007). In HRI, it is essential to consider both the technical and human-centered requirements in order to achieve the best results in work system design (Dautenhahn, 2007). In addition, HRI aims to optimize cooperation processes by improving transparency and consistency, and establishing higher safety levels within a given work system. These improvements are often combined with other interventions, such as the optimization of logistics and inventory control (Morioka and Sakakibara, 2010).

In the last 30 years, there has been a significant increase in HRI research. This increased focus on HRI has spawned a broad variety of new robotic capabilities leading to improvements in the use of resources and the ability to fulfill human needs; e.g., in the fields of helper robotics (Kimura et al., 1998) and manufacturing assistance (Kristensen et al., 2004; Stork et al., 2007). However, there has been little focus on direct human-robot cooperation in industrial work systems. HRI in industrial assembly systems is aimed at developing a positive relationship between human and robot in terms of occupational health and safety, as well as improving human performance and enhancing productivity (Hägele et al., 2004). Direct HRI is usually investigated in scientific studies based on prototype systems within continuous laboratory environments. This improves the relationship between human and robot by focusing on the level of mutual cooperation. The design of direct HRI needs to focus on two aspects, namely physical HRI (pHRI) and cognitive HRI (cHRI) (De Santis, 2007). On one hand, pHRI is relevant through the emphasis on health and safety issues related to the human musculoskeletal system, and on ergonomic solutions integrated into a user-centered design process of the physical functions and form of the work area. When regarding this physical aspect, all phases of robot design and robot control must be considered. On the other hand, cHRI considers the central processing components of human information processing when interacting with robots (Stubbs et al., 2006; De Santis, 2007) and is therefore only relevant for the design and evaluation of the relevant control algorithms. Mayer et al. (2009) carried out a cHRI study that focused on the cognitive compatibility of the production rules in the knowledge base of an articulated robot, and the human procedural knowledge in an automated assembly cell.

To evaluate the effects of automation functions in a work system, the definition of the term "automation" is required. Automation is defined as "automatic control of the manufacture of a product through a number of successive stages; the application of automatic control to any branch of industry or science; by extension, the use of electronic or mechanical devices to replace human labor" (OED, 2010). Referring to the extended definition of automation, "human labor" in automated work systems is not habitually replaced. The role of human operators in highly automated systems is essential, especially to carry out various kinds of supervisory control tasks, or to intervene whenever errors occur (Mayer et al., 2012). Hence, future manufacturing systems should focus on the integration of human operators in the production environment according to his or her specific capabilities in problem solving, decision making and planning (Schlick et al., 2002).

The need for developing the skills and knowledge of experienced machine operators also encourages the design and application of ergonomic human-machine interfaces (Luczak et al., 2003). When based on an ergonomic human-machine interaction, an operator can easily evaluate the given situation and state of the system, and is therefore able to break the vicious cycle of automation (Onken and Schulte, 2010), an observation previously introduced by Bainbridge as the "ironies of automation" (Bainbridge, 1983). In this cycle, a human operator function is automated due to poor human reliability. The automation causes a higher function complexity, and therefore increasing the demands on the human operator in terms of planning, teaching and monitoring. This situation leads to a more error-prone system. To reduce the number and consequences of potential errors, an extended automation is performed, which in turn reinforces this vicious circle. During the first cycle of robotic automation, it is possible that the overall performance of automated system increases, but the potential risk taken is often ignored or severely underestimated. Additional automation cycles usually result in performance deterioration and poor solution choices. Therefore, the human worker should be considered as an integral part of automation, leading to a joint cognitive system (Hollnagel and Wood, 1999) in which the technical function and human operator skills act as one integrated system. Furthermore, the cooperative control with an emphasis on the cooperation between human and technical system in a highly automated system such as highly automated vehicle will leads to human-centered automation that improve human understanding towards the structure of highly automated system (Flemisch et al., 2004).

Human workers fulfill an essential role in production systems and feature individual methods, strategies and procedures when carrying out their respective work tasks. In a joint cognitive system, they fulfill a combined role of operator and system supervisor. Therefore, they should be able to effectively make decisions, support the team in the work system and autonomously conduct actions, especially in situations critical to safety or quality. Thus "cognitive patterns", as high-level structures of cognitive control, are critical points in these work systems because a large part of system performance is dependent on human cognition. This human-oriented symbolic representation is used as a basis of cognitive planning and control system design.

Cognitive control in production systems can be applied in different areas, e.g., assembly or logistics. The follow on from this study would be to further optimize production systems by focusing on decision making and reassigning in detail, i.e. robotized assembly processes. Assembly processes represent a part of the production system where the cognitive control concept becomes an especially valuable guide in building a flexible and anticipatory joint cognitive system. In this area, the goal-oriented cooperation between the technical system and the human operator is essential. Therefore, it is necessary to develop a predictive model for human-machine cooperation that enables the cognitive control system to be operated effectively and safely by highly skilled operators in high-wage countries. Thus, the design of the cognitive control system should focus on the compatibility between the human operator and the technical system on all levels of cognitive control in the sense of Rasmussen (1986). Rasmussen (1986) defines three levels of cognitive control: the skill-based level, rule-based level and knowledge-based level. Action regulation on the skill-based level is based on stored information and occurs without conscious control. This refers to highly routinized actions where a 'signal' is enough to trigger the appropriate reaction. Performance on the rule-based level is determined by memorized rules of procedures and past experiences. An appropriate rule is activated by the recognition of a previously encountered situation. In a situation that has not been previously encountered, new responses are planned and adapted to on the knowledge-based level. Declarative knowledge is consciously analyzed to generate a behavioral strategy.

A new design of a cognitive control system called a cognitive control unit (CCU) is based on an architecture of human cognition. It has been developed to achieve a better compatibility between the human mental model and the knowledge base of the robot. A CCU is assigned the coordination of seemingly non-value-adding tasks (i.e. low-level control programming) are transferred from high-expertise workers to the robot. By doing so, the CCU can reduce the burden of repetitive, simple, and dangerous tasks on human operators. It allows the rule-based processing of events in a production system (Mayer et al., 2009; Buescher et al., 2012). The CCU can also autonomously plan assembly processes and react effectively to ad hoc changes, based on a self-developed set of production rules within its knowledge base. This means that rule-based human behavior can be simulated leading to self-optimizing assembly processes (Mayer et al., 2011).

The conceptual development of self-optimization is driven by the necessity for an integrated approach to production systems, so that an inappropriate, single-element focus can be avoided. A self-optimizing system can adapt its objective based on the situation at hand and is able to rely on its simulated cognition to carry out this adaptation. Its symbol processing system is (semi-) autonomously capable of planning and learning from its own experience (Mayer et al., 2008). A self-optimizing production system attempts implementations based on value-oriented approaches while increasing planning efficiency through its ability to reuse knowledge gained from having to deal with new production conditions (Hauck et al., 2008). The focus on self-optimization requires a goal-directed behavior simulation that is based on the cited architecture of human cognition (Mayer et al., 2011). Self-optimization concepts are also expected to improve the conformity of operator expectations regarding CCU decision-making. They lead to a more flexible supervisory control in a work system and to the transferability of human cognitive patterns to the CCU.

Conventional research in ergonomics often treats participant cognition as a static factor within the system. This conventional approach contradicts the user-centered design of human-robot systems where participants experience a change in cognitive processes through their contextualized learning experience with the robot(s). Changes in cognitive processes reflect the adaptation of the participants' mental model in the human-robot system and the participants' understanding of broader concepts within robotics. Stubbs et al. (2006) emphasize that a mental model also represents a dynamic idea of a system that is shaped and limited by the individual's conceptual knowledge.

To ensure conformity of the operator's expectations with the technical system during the supervision of robotic assembly processes (Mayer et al., 2008), the first step in the design process is to use motion descriptors of the hand-arm system for planning and executing the assembly steps within the CCU. This design is based on premise that the repetitive motions of hands and arms are familiar to the human operator through training in manually performed assembly tasks (Gazzola et al., 2007). When processing a supervisory task, however, the human operator is continually monitoring the activities in the system, and comparing them with his/her mental model. Based on the human mental model, expectations for the following activities can be formulated and compared to observations of the system state. When the knowledge base of the CCU is extended by integrating production rules based on human heuristics, the robot's build-up sequence can be better anticipated by the human operator. Moreover, it is more compatible with his/her procedural knowledge of the assembly process and leads to less errors and lower levels of stress (Mayer and Schlick, 2012).

Mayer (2012) carried out a laboratory study to verify the predictability of robot behavior when assembling plastic LEGO bricks. This empirical study took human assembly strategies into account. Here, work regarding the predictability of robot behavior and the development of the human-machine interface represent the foundation for this thesis.

Based on this formulation, additional studies are conducted that conceptually improve previous results. The first empirical study is a continuation of Mayer's experiment, whereby the scope of the experiment is broadened through considering additional independent variables, such as the different cultural backgrounds of the participants. Asian and European cultural backgrounds are investigated. Additional independent variables are: different cognitive models in controlling robot behavior during assembly; different kinds of assembly information; and different kinds of assembly groups. The objective of this new study design is to further improve the conformity of the operators' expectations and to verify the previous findings (Mayer, 2012). It also aims to improve direct human-robot cooperation, by initially using a simple LEGO product as the assembly product model. Human assembly strategies represented in the cognitive models concerned are further elaborated in a second study. This study focuses on the transferability of the developed cognitive model to other assembly tasks and investigates the influence of age and cultural backgrounds of the participants.

In the second empirical study, the identified strategies initially involved in assembling the simple LEGO product are then transferred to the assembly of a manufactured product – namely a carburetor. The study objectives are: to replicate the findings of the first study with a functional manufactured product instead of a LEGO product model; to transfer the human-oriented design concepts in the knowledge base of the CCU from a model world to an industrial environment; and to evaluate human behavior in detail using an eye-tracking system. This second empirical study is based on different cognitive models for controlling robot behavior and different kinds of assembly groups. It also focuses on changing demographic conditions, namely the ageing working population and their different cultural backgrounds. The changing of the population pyramid with regard to rapid ageing is an important factor in designing a work system compatible for both Western and Eastern countries. The second study makes a detailed examination of the influence of different age groups (an older and a younger group) and cultures (Indonesian and German) on self-optimizing assembly systems.

Both empirical studies are carried out according to the user-centered design paradigm, which addresses the cognitive compatible design of production rules in the knowledge base of the CCU. This approach ensures that the CCU can plan and execute robotized assembly processes in accordance with operator capabilities. It is expected that a human-centered CCU design can significantly improve the compatibility between the system behavior and the human operator's expectations.

1.2 Research Questions

The goal of this thesis is to create and verify scientific knowledge about the user-centered design of a cognitive control unit for self-optimizing robotic assembly cells. By conducting laboratory studies under controlled conditions, it is possible to analyze, model and simulate human cognition in assembly processes with robotic systems in detail. The obtained cognitive simulation models can also be directly applied to the prototype assembly cell. Based on these models, robot behavior in the work system will adapt to human cognition in a closed loop in order to: improve planning efficiency; find near optimal solutions to problems caused by changes in the work system environment; and improve the learning process based on prior knowledge and experience. Hence, the three most important research questions of this thesis are:

1. *Based on an architecture of human cognition, how can a robot simulate human rule-based behavior so that it can adapt to the changing conditions of the assembly environment and also simulate human assembly heuristics to improve conformity to operator's expectations?*
2. *How can the human assembly strategies be identified, encoded in the terms of production rules and transferred from a model product into a manufactured product?*
3. *How do age and cultural background influence human performance, reliability and subjective mental workload when interacting with the CCU of a self-optimizing assembly cell?*

1.3 Structure of the Thesis

To answer the formulated research questions, it is necessary to carry out an extensive literature review about the main variables examined in this thesis. The background (Chapter 2) is provided to describe and explain the relevant societal, organizational, technical and ergonomic conditions for self-optimizing robotic assembly cells. Concerning societal conditions, it is necessary to put the age-differentiated and cross-cultural design of work systems into focus as a central demographic aspect. Since many countries in the world are experiencing a disproportionate aging of the population, relevant companies will be affected by changing age structures of their working populations. An aging population usually leads to a decrease in the availability of younger workers. In order to achieve an effective and safe work system design in response to this phenomenon, the current situation of older employees in work systems must be taken into account (Chapter 2.1). In more detail, the ageing effect on the different regions in the world such as Germany (as a high-wage country) and Indonesia (as a low-wage country) has to be taken into consideration. An analysis of human performance has to be carried out to examine whether the designed self-optimizing assembly system can cope the disparate ages of the workers involved.

The second central demographic aspect refers to the cross-cultural design of work systems (Chapter 2.2). The cross-cultural design of work systems is essential in order to understand and evaluate the various predispositions bound to each culture in relation to the manufacturing system. The general cultural differences in work systems are represented by people of European (Western) and Asian (Eastern) origin, since competition in manufacturing is centered around these world regions. Study 1 considers different cultural background as an independent variable. In order to investigate the effect of different cultural backgrounds on the manufacturing system in more detail, study 2 compares human performance, reliability and the subjective mental workload of participants from Germany (as an industrialized country) and Indonesia (as a developing country). Considering the differences between these cultures is of great importance in the design of self-optimizing assembly systems, since the productivity of the human operator can be significantly different based on their cultural background.

To support the fundamental understanding of the central components of human information processing, human cognition is analyzed in detail in Chapter 2.3. The human cognitive system and decision-making processes are the most important elements when evaluating human performance during assembly work. The analysis of human cognition is required to identify the human assembly strategies when working with the CCU. Furthermore, comprehension of human cognition enables an understanding of the conceived recognition and decision making involved, most particularly when human operators interact with technical systems and perform prediction tasks.

In order to comprehend the influences of age and culture on human cognition, it is necessary to examine the differences in human cognitive processes during work in detail. Chapter 2.4 reviews the effect of different ages and cultural backgrounds on human cognition, especially in manufacturing systems. This analysis is necessary to find out whether different demographic conditions affect human perception and decision- making processes when working in similar assembly environments. It is also required for ascertaining whether different ages and cultural backgrounds lead to significant differences in human performance.

In order to analyze the control function of human cognition in a more specific way, it is necessary to review normative models of human cognitive control. In Chapter 2.5, a general framework of human cognitive control related to a technical system is provided. This chapter is required to investigate how the cognitive control system affects the response and decision making process during assembly. This chapter also provides a theoretical contribution to the cognition-oriented design of a representative technical system. The focus here is also the application of CCU as a very flexible controller. Therefore, it is necessary to review different representations of human cognitive control in technical systems. Chapter 2.6 comprehensively describes the preferred formal approach. With this review, the development of a cognitive technical system is taken into account.

To obtain a scientific foundation for solving problems arising from changes of environment and operator conformity, a theoretical review of cognitive control in self-optimizing assembly systems (Chapter 2.7) is carried out. This chapter also explains in detail the design of the CCU as a symbol-processing system and its application in a self-optimizing assembly cell. An operator understanding the basic mechanisms of the CCU is very important for carrying out a user-centered design of the assembly work system, since work systems require compatibility between human expectations and the technical system. To achieve the objective of this thesis regarding the user-centered design of a CCU in a self-optimizing assembly system, it is necessary to understand the concept of user-centered design as a basic theory of system design. Chapter 2.8 discusses the specific requirements of this system in both human-robot interactions and robotic assembly systems in detail. This topic is necessary to investigate whether the designed work system fulfils requirements and satisfies users.

The last topic of the background chapter is the analysis of CCU implementation in self-optimizing assembly systems (Chapter 2.9). In this chapter, the development processes and previous implementations of a CCU in robotized assembly systems are carried out. Additionally, a current study, in this field on the design of cognitive simulation model is also described. To verify the previous findings and examine the applicability of the CCU in more complicated assembly environment, the experimental design of this thesis is further defined and elaborated on based on the analyses of these topics.

To achieve the objective of the studies, detailed methods and experimental design are required. In Chapter 3.1, Study 1 focuses on the transfer process of human rule-based behavior to a robotic system. This study is carried out under controlled laboratory conditions. Study 1 is conducted to evaluate and verify previous findings from simulations of human assembly heuristic when the assembly environment is elaborated with additional independent variables such as the different models of robot behavior, assembly groups, length of the prior assembly sequences and cultural background. An analysis of study results related to human performance in prediction tasks is then conducted to examine whether the simulated rule-based human behavior with different independent variables improves the conformity of operators' expectations.

In order to validate the result of Study 1 and answer the second research question, it is necessary to conduct a second study focusing on the identification and transfer process of human procedural knowledge from the model product used in the first study to a real manufactured product. Therefore, Study 2 (Chapter 3.2) is required to examine whether the simulated human assembly heuristic is also applicable in assembling a more complicated product such as a carburetor. Furthermore, Study 2 also investigates the influences of age and culture on human performance when interacting with the CCU. Therefore, the independent variables in Study 2 are: the models of robot behavior; assembly groups (LEGO product and carburetor); and the cultural backgrounds and ages of the participants. To answer the third research question, it is necessary to discuss (Chapter 3.3) the consolidated findings based on the results of statistical analyses. Here, the influences of age and culture on participant performance, as well as the role of CCU in user-centered design in self-optimizing assembly systems is taken into account.

The answers to the raised research questions are summarized in the conclusions (Chapter 4.1). Finally, potential for future work is described in Chapter 4.2 to establish the next research topic related to the results of these studies. An overview of the structure and content of this thesis is given in Figure 1.1.

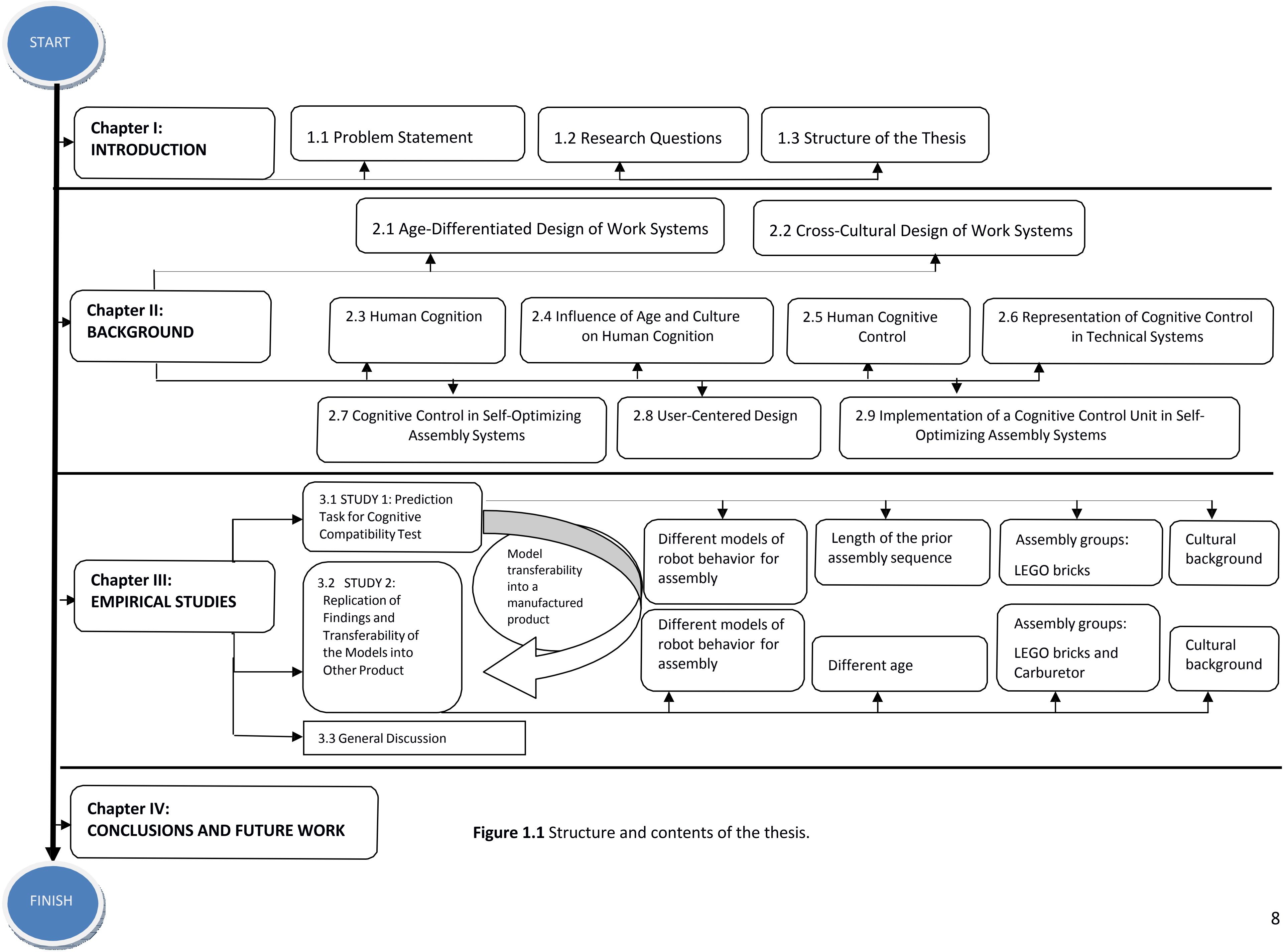


Figure 1.1 Structure and contents of the thesis.

2. BACKGROUND

2.1 Age-Differentiated Design of Work Systems

The first demographic trend that should be considered in the user-centered design of production system concerns workers' ages. Both in Western and Eastern cultures, working ages are a primary focus in long-term work system design. This section provides a detailed comparison of the working age population of European (especially Germany) and Asian countries (especially Indonesia).

The structure of the world population is changing significantly as is indicated by the population pyramid shape (see Figure 2.1). Approximately 810 million persons were aged 60 years or over in 2012. This number is projected to grow to more than 2 billion by 2050. For the first time in human history, there will be a greater number of older persons than children (0-14 years) (see Figure 2.2). About 55% of the world's older persons live in Asia, and Europe accounts for 21% of the total. As depicted in Figure 2.2, the development of the global population has a greater similarity to that of less developed regions than to more developed regions. Less developed regions include Africa, Asia (excluding Japan), Latin America and the Caribbean, as well as the regions of Melanesia, Micronesia and Polynesia. More developed regions include all regions of Europe and Northern America as well as Australia, Japan and New Zealand (United Nations, Department of Economic and Social Affairs, Population Division, 2012).

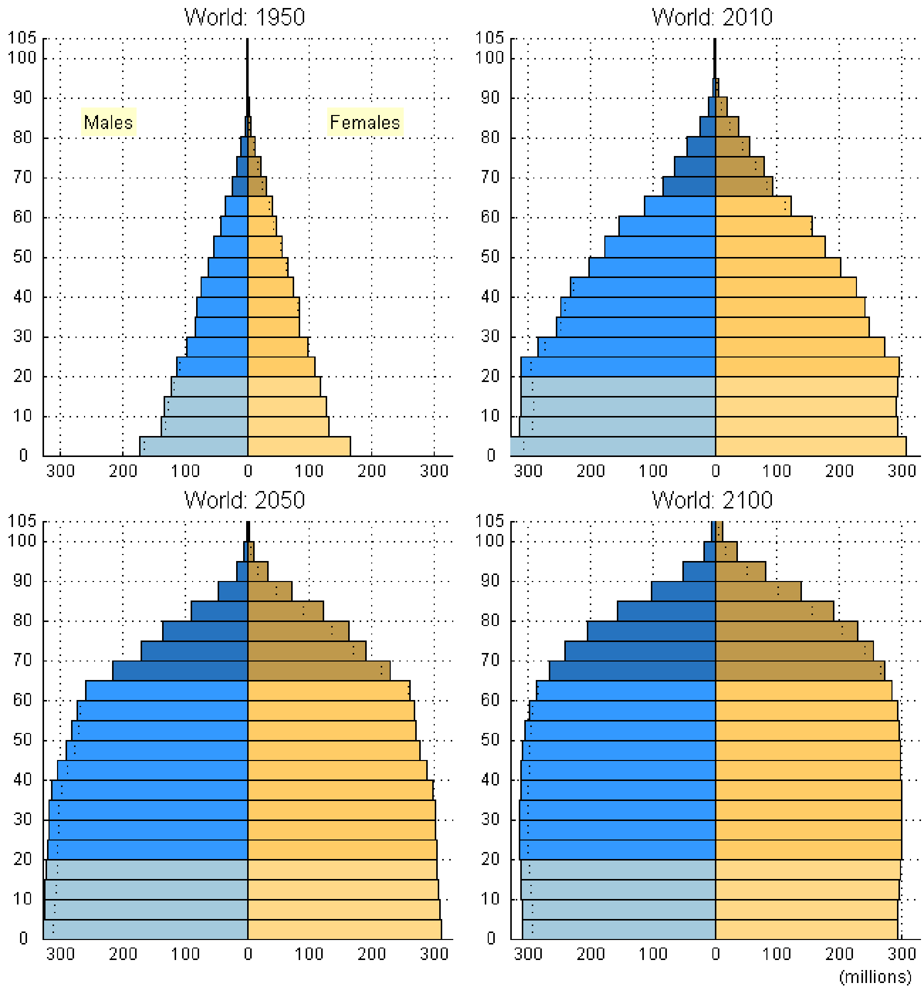


Figure 2.1 World population by 1950, 2010, 2050 (estimation) and 2100 (estimation) (United Nations, Department of Economic and Social Affairs, Population Division, 2011).

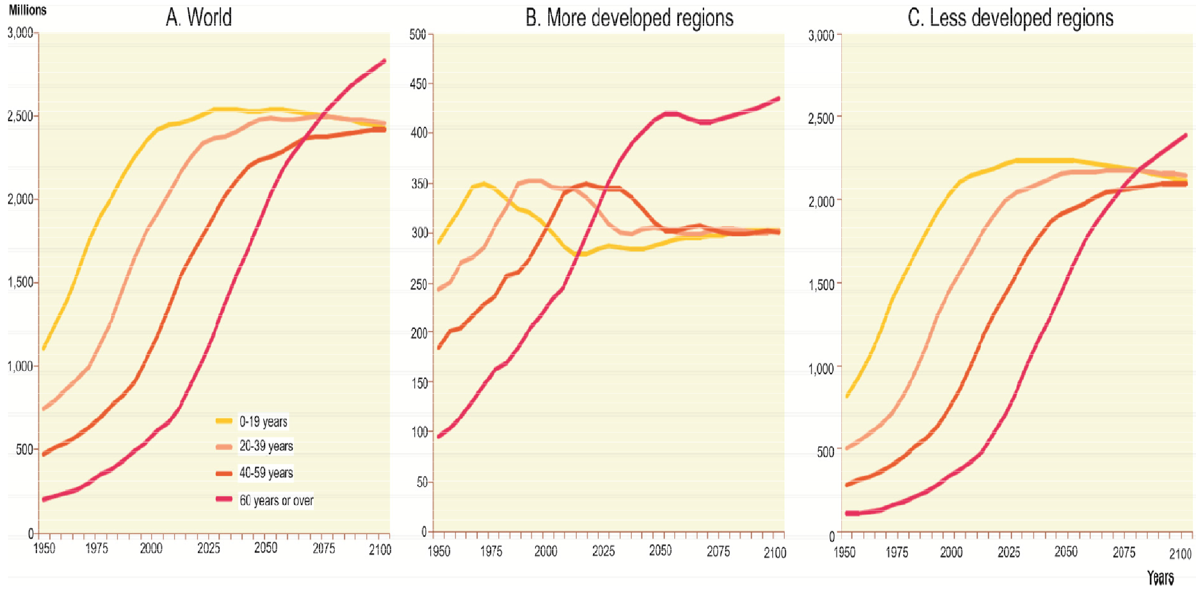


Figure 2.2 Population by broad age group (United Nations, Department of Economic and Social Affairs, Population Division, 2012).

According to Desjardins and Warnke (2012), ageing is one of the main factors in Organization for Economic Co-operation and Development (OECD) policy establishment. Statistic data from OECD (2006) highlights that about 33% or more of the population in Italy, Japan and the Republic of Korea, as well as about 20% or less in Mexico, Turkey, and the United States, are projected to be aged 65 or older in 2050. It can be concluded that most countries in the world are facing the ageing trend.

Specifically, the average age of workers in most of the industrialized countries has increased rapidly (Toosi, 2007; Göbel and Zwick, 2011). For example, Börner et al. (2012) state that one third of the working population in Germany will be older than 50 years in 2030. This represents a phenomenon in which the age of the working population is increasing, but in contrast, the number of those reaching working age is declining (Nägele, 2007). Simultaneously, after 2015, the baby-boomer generation will no longer be of working age. This will not only cause a decrease of potential employment, but also raise the proportion of active older workers. Therefore, companies in Germany should consider this demographic condition in order to ensure their competitive ability and preserve their productivity. Figure 2.3 compares the demographic structure of the German population in 1950, 2010, 2050 (estimation) and 2100 (estimation).

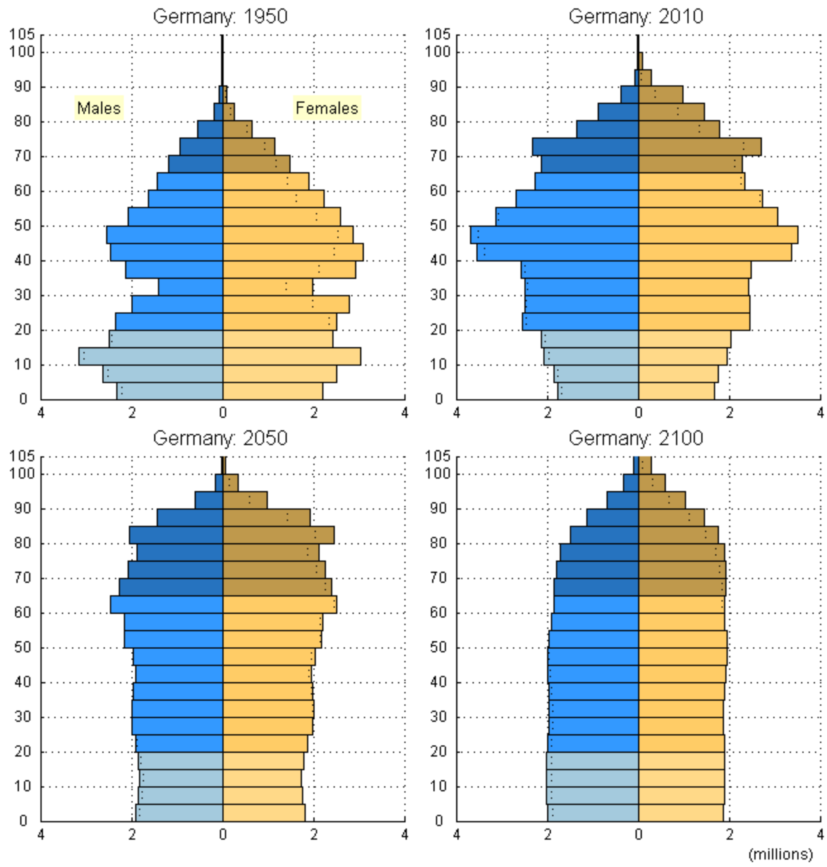


Figure 2.3 Demographic structure of German population in 1950, 2010, 2050 (estimation) and 2100 (estimation) (United Nations, Department of Economic and Social Affairs, Population Division, 2011).

In Asia and the Pacific, the number of elderly people has grown rapidly from 410 million in 2007 to 733 million in 2025, and is estimated to become 1.3 billion in 2050 (ILO, 2010). The population of East Asia (e.g. China and Republic of Korea) shows similar developments. As stated by International Labor Organization (ILO, 2012), "By 2030, the old-age dependency ratio is projected to jump from 15.9% to 37.3% in the Republic of Korea and in China from 11.6% to 23.9%".

For a while, Indonesia will have demographic age structure advantage. By 2010-2025, most of the Indonesian population will fall into an age bracket favorable for labor forces. This should be regarded as an advantage and an enhancement of the human resource quality (Kontan, 2011). However, after 2025 the Indonesian population will experience similar problems to those currently observed in Europe and most other countries. By 2020, the older age population is estimated to reach about 28.8 million (about 11% of the total population) (ILO, 2010). Figure 2.4 shows the development of the Indonesian population by 1950, 2010, 2050 (estimation) and 2100 (estimation).

A comparison of the median age in Western (Germany) and Eastern (Indonesia, China, Japan and Republic of Korea) populations is shown in Figure 2.5. The divergences in less developed regions and more developed regions are depicted in Figure 2.6. In the less developed regions, the population is switching from a triangular, wide-based shape (related to a youthful age structure) to a more rectangular shape (related to an older age structure). The age composition of the more developed regions is also in an interim state, from a rectangular shape in 1970 to the even more rectangular structure in 2050 (United Nations, Department of Economic and Social Affairs, Population Division, 2012).

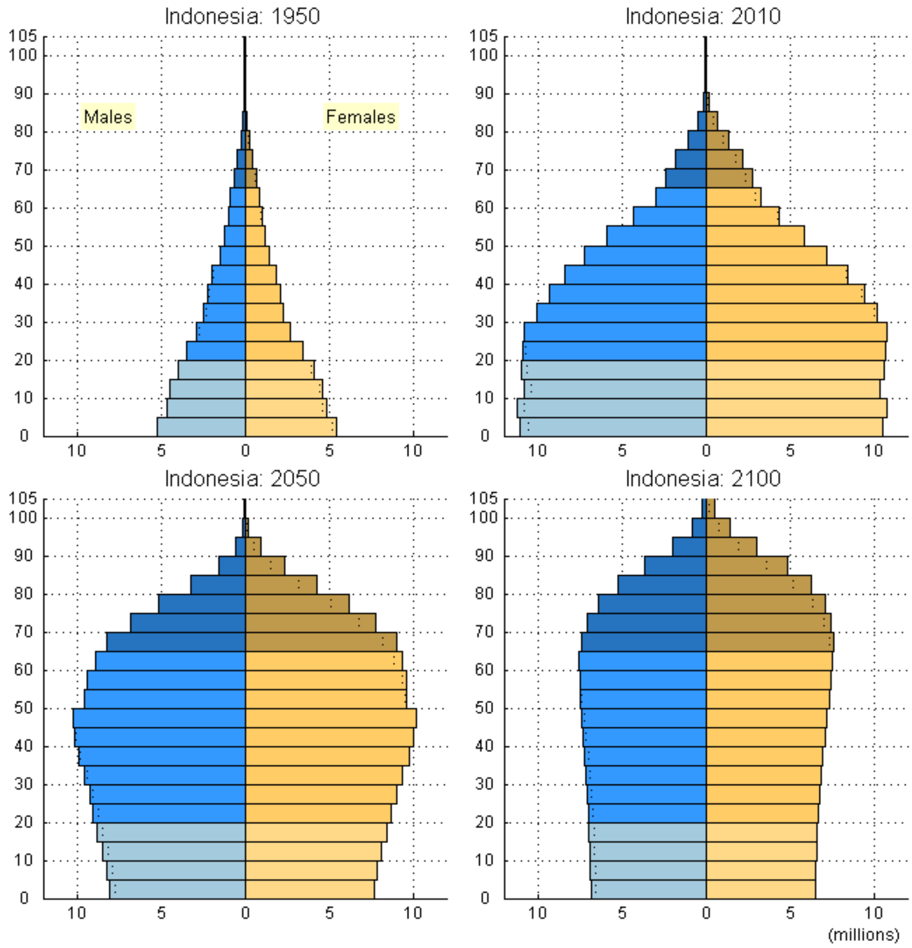


Figure 2.4 Age structure of Indonesia's population: comparison between 1950 and 2050 (United Nations, Department of Economic and Social Affairs, Population Division, 2011).

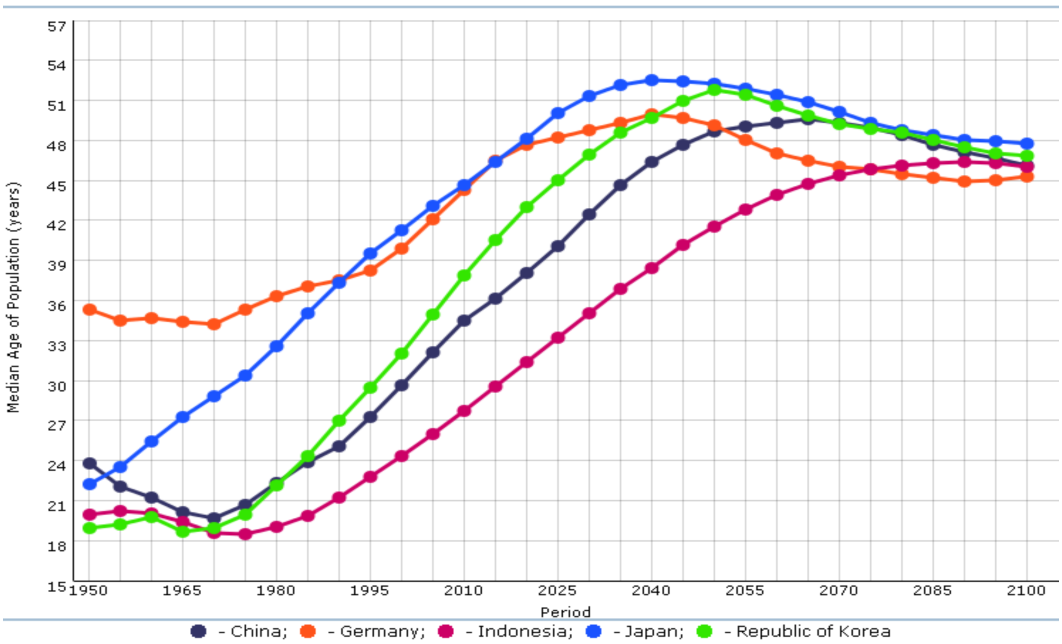


Figure 2.5 Median age of the population in China, Germany, Indonesia, Japan and Republic of Korea (United Nations, Department of Economic and Social Affairs, Population Division, 2011).

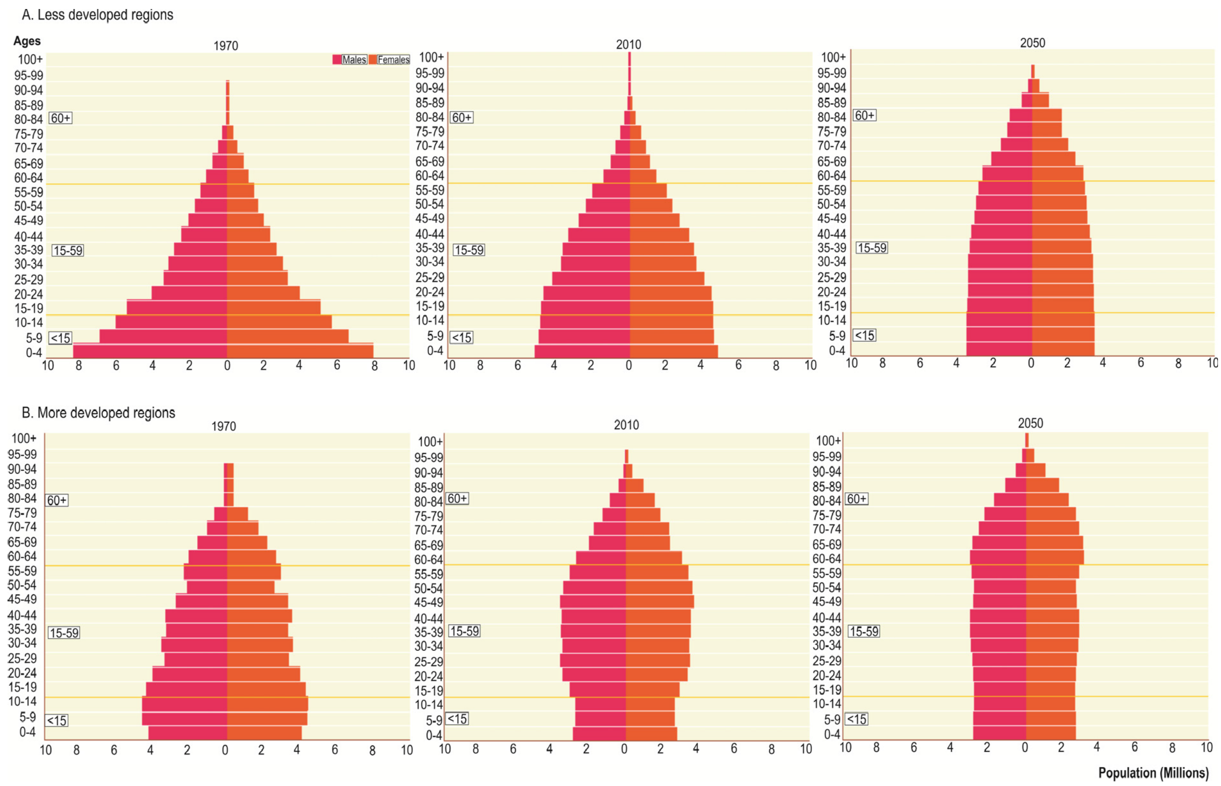


Figure 2.6 The comparison of the population pyramid of less developed regions and more developed regions (United Nations, Department of Economic and Social Affairs, Population Division, 2012).

It is foreseeable that all countries will be confronted with an ageing of their populations. With regard to this fact, the second study explores the ability of work system design with regard to the variation of the age of the worker population. The performances of two groups of workers (older and younger) are probably not comparable. However, an exemplary work system design is expected to be able to accommodate and adjust the system to differentiations in the ages of the workers.

2.2 Cross-Cultural Design of Work Systems

The second notable demographic aspect presented in this thesis concerns the cultural differences between European and Asian countries. As European and Asian countries occupy crucial roles in world trade and production systems (see Figure 2.7), the competition between the two sides is inevitable.

European countries, such as Germany, Netherlands, France and Italy, are at the top of the world trade record regarding their export-import and commercial services. They intensely compete with Asian countries, such as China, Japan and Korea (WTO Secretariat, 2012). As stated by the World Bank (2012), Germany can be seen as a high-wage country together with United States, Japan, Netherlands and other countries, while China is a lower-middle-wage country.

Remarkably, high-wage countries compete with low-wage countries on world trade markets. The competition between high-wage and low-wage countries can be concisely summarized by two economical dimensions namely production-oriented economics and planning-oriented economic system causing the polylemma of production (Buescher et al., 2012).

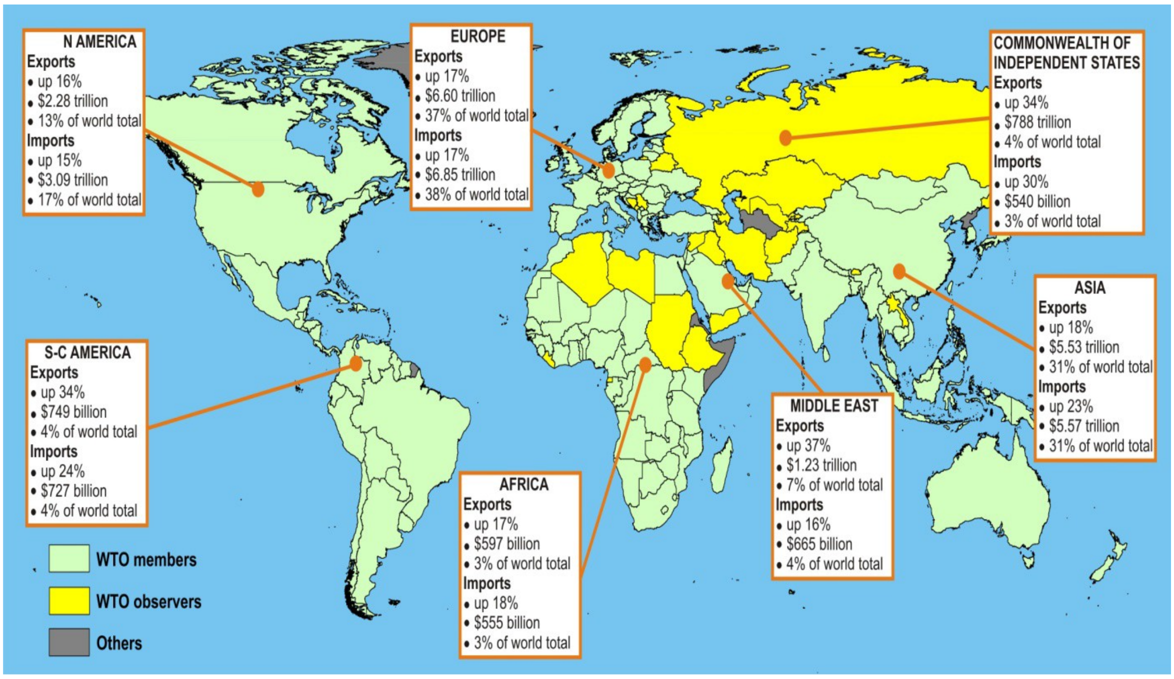


Figure 2.7 Merchandise exports and imports by region (WTO secretariats, 2012).

The first economic dimension describes how the production systems of low-wage countries provide reasonable compensation for potential disadvantages through a lower cost factor of production periods, factor expenditure, and process mastering. In contrast, company systems of high-wage countries try to capitalize on the economies dimension that consumes the rather costly production factors. Furthermore, high-wage countries are forced to attempt, customize, and rapidly adapt to the market requirements. Hence, the contribution of production in the value chain and feasible economies-of-scale are progressively reduced. In the second dimension, high-wage countries encounter further competitive disadvantages. Companies in high-wage countries continually aim at high levels of process optimization by using complicated and investment-intensive planning and process production systems while companies in low-wage countries realize an effortless and "robust values-stream-oriented process chain" (Klocke, 2009).

To survive and create competitive advantages, a work system design that accommodates customer demand should be identified and specified. One approach for solving the production polylemma in this competition is the design of a self-optimizing assembly cell. It integrates the flexible automation concept based on robot utilization and human-robot interaction with regard to human cognitive mechanism.

Robots are increasingly utilized in production systems as a competitive way to resolve the production polylemma. Asian countries such as China have become the most dynamic market in 2010 with almost tripled robot sales compared to other regions in 2010 (IFR Statistical Department, 2012). The annual supply of industrial robots to growing markets in 2008 to 2011 is followed by the Association of Southeast Asian Nations (ASEAN) regions such as Indonesia, Malaysia, Philippines, and others Asian countries. Currently, the automation ratings based on robot supplies during 2008 and 2011 are occupied by Japan (increased 27% from 2010), the Republic of Korea (increased 9% from 2010), China (increased 51% from 2010), United States (increased 43% from 2010), and Germany (increased 39% from 2010). This evidence suggests that the competitiveness of automation in the production systems between Asian and Europe will strongly increase in terms of product quality and price.

The number of cultural studies on work systems has been rapidly growing, particularly concerning work culture. Eastern and Western systems are particularly different, especially regarding patterns of approaches to robot and human resource utilization in the automation of a work system. From the ergonomic point of view, cognitive differences in human cultures lead to divergent designs of work systems, which are based on human ability and adaptation to the environment. Cultural differences as well as a cognitive process distinction due to cultural practice initiate a method to solve this problem (Nisbett and Norenzayan, 2002).

As part of the widespread industrialization, the Western population is highly educated and prefers logical reasoning while the Eastern population prefers actual, spontaneous and "knowledge-based reasoning" (Nisbett and Norenzayan, 2002). Nisbett (2003) distinguishes Eastern and Western cognition based on their perspectives and worldviews. East Asians tend to observe the world as a complicated and continually altered situation while Westerners have a tendency to control their situation based on their confidence ability. If these concepts are applied to an international work system, as a consequence, it has to be an "error tolerant" system that supports the divergent flow of logic and information instead of providing different equipment for different cultures (Tam and Dulley, 2005). Therefore, designers are expected to be more attentive to the variations in the cultural backgrounds of workers.

In perceptual processing, a cultural discrepancy in thinking mechanisms is observed between Easterners and Westerners. Norenzayan et al. (2007) explain that holistic-thinking of Easterners is related to a high degree of interdependence while the analytic thinking of Westerners is explicable in terms of the high degree of independence. This hypothesis is consistent with the difference between an individualistic culture style (e.g. the United States and Germany) and a collectivistic culture model (e.g. Russia and Malaysia) (Kuhnen et al., 2001).

A series of cultural studies reviewed by Tipandjan (2010) confirms the differences in decision-making process between German and Indian students. The results indicate that the German students' strategy is "expansive-risky (stable decision-making strategy)" while the Indian students' strategy is "defensive-incremental (flexible decision-making strategy)". These findings highlight the different behavioral patterns in decision making between students from France, Germany, and Norway compared to their colleagues from India, Indonesia, and Malaysia (Mann, 1998).

The aforementioned cultural differences influence the design of a work system and the cognitive system should be considered in a cross-cultural study as well. A work system design is expected to maintain a high level of worker performance regardless of the different cultural systems. In this thesis, specifically the divergence between Easterners and Westerners is discussed. Study 1 focuses on the divergence between Asians and Europeans while Study 2 examines the differences between German and Indonesian in detail. This study examines the effect of European (especially German) work system design on worker performance, as well as the verification of the generality of the work system design.

To sum up, both the cultural aspect and the age factor are essential aspects in designing a work system. Therefore, the independent variables of this study consider these factors to investigate the influence of both factors in the work system and to examine the general applicability of the work system design.

From the study of demographic background, it can be hypothesized that by using a cognitive control unit based on human procedural knowledge reflecting cognitive effects of aging and cultural background, a feasible work system for self-optimizing assembly systems can be constructed.

2.3 Human Cognition

According to the Oxford Learning Dictionary, “cognition is the process of obtaining knowledge through thought, experience, and the senses”. Derived from the Latin word “cognoscere”, cognition means “to consider” – in the sense of “to think deeply on” – knowing or apprehending through the understanding of something. A cognitive system is capable of the cognitive activities of realizing, understanding, planning, determining, problem solving, analyzing, integrating, examining, and judging as they are fully integrated with perceiving and acting (Lintern, 2007; Larsen, 2008). Vernon et al. (2007) explain that cognition itself can be viewed as the process of a system to achieve robust, adaptive, anticipatory and autonomous behavior entailing embodied perception and action. Thus, it can be said that human cognition is a configuration process in human behavior based on the human cognitive ability.

2.3.1 Cognitive Psychology

Cognitive psychology discusses how mind and body achieve harmonious coordination. It also examines the way intelligent thinking is generated or how the process of thinking becomes observable in the brain (Gamrad, 2011). Technological development encourages modeling and simulating human cognition with user interfaces rather than merely carrying out the classic ergonomic design. Equipment such as a functional Magnetic Resonance Imaging (fMRI) is employed to visualize the process of thinking in the human brain. It maps neural activity from the alteration of blood flowing within the brain. Figure 2.8 shows the horizontal view of the human brain.

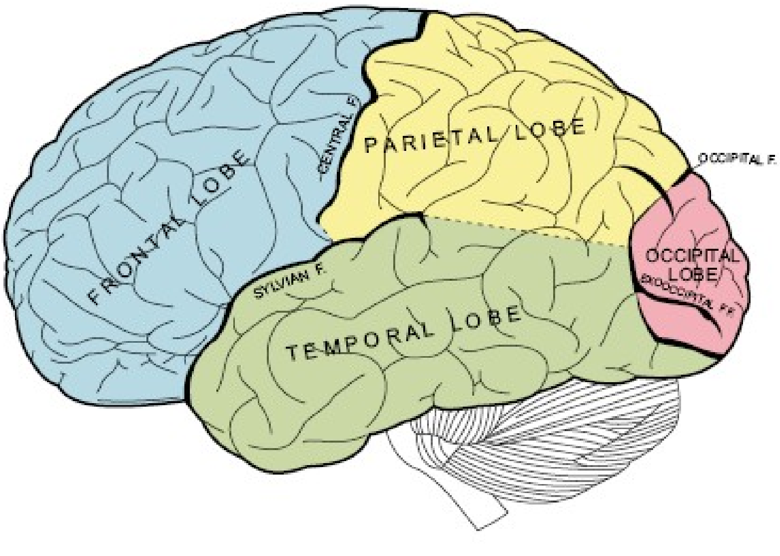


Figure 2.8 The principal fissures and lobes of the cerebrum (Gray, 1918).

The brain branch is the oldest part of the human brain. It is located in the lower part and comprehends basic reflexes. The cerebellum is located in the lower right part and is partially responsible for the representation of highly trained skills like bicycling or speaking. The youngest part of the human brain regarding human evolution is the cerebrum, which is required for higher cognitive functionalities. The cerebrum can be divided into primary and associative areas. The primary areas are related to information from a particular brain part. For example, the visual area is located at the back part of the occipital lobe, and the auditory areas are located at the temporal lobe. The associative areas combine the information from various primary areas. Finally, the primary somatosensory cortex for the sense of touch and the primary motor cortex for the planning and execution of movements are located side by side at the central fissure (Gamrad, 2011).

2.3.2 Human Information Processing

Cognitive skills are used in the process of understanding. There are four steps of human cognition (Chen, 2004). First, humans acquire new information. Second, they reflect on this new information. Afterwards, they translate it into their own words. Finally, they will notice how this new information conforms to prior information stored in the brain. The learning and integration of new information process determine whether humans will successfully develop their cognitive skills. These steps are termed human information processing. Figure 2.9 depicts how human information processing works.

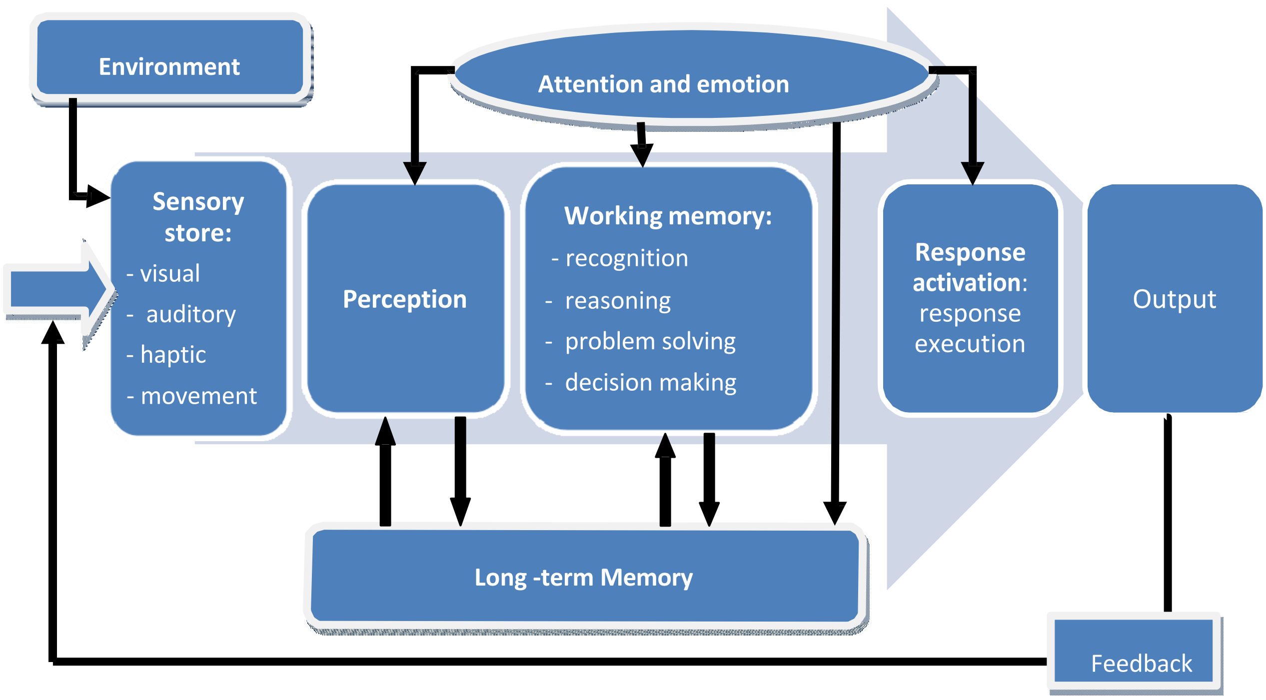


Figure 2.9 Human Information Processing (Chen, 2004).

Different phases in human information processing describe the sensations and perceptions from which humans obtain information about the world and the environment. A sensation is obtained through human senses such as the eyes (visual sensation), the ears (auditory sensation), the nose (olfactory sensation) and other sensory organs. These sensory receptors recognize raw or stimulus energy which is converted into neural signals through a transduction process. Afterwards, the neural signals will be sent to the brain. In the perception phase, neural signals are selected, organized and interpreted. Figure 2.10 describes the process of sensation and perception (Kassin, 2004).

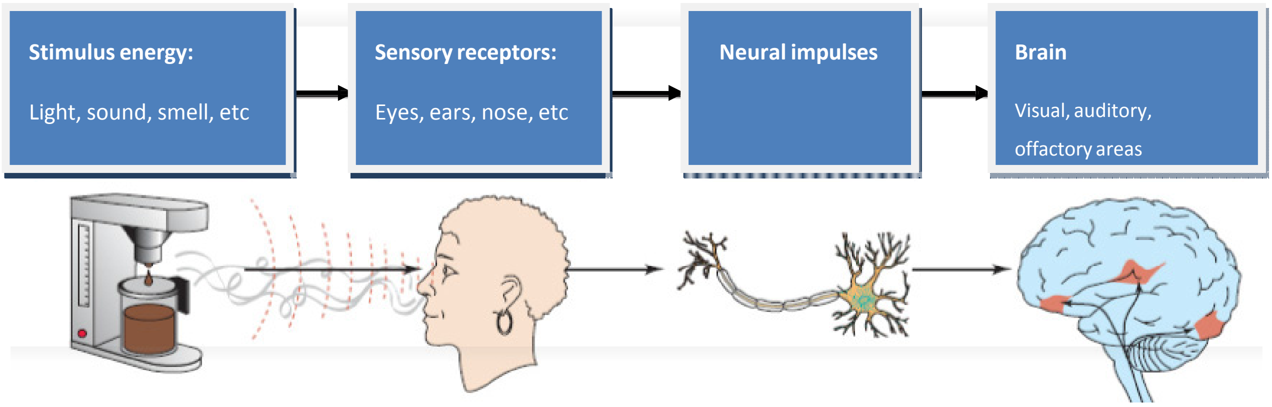


Figure 2.10 The process of sensation and perception (Kassin, 2004).

A sensation is finished by a reaction of the numerous bodily sensors. For example, sensors found in muscles are muscle and tendon receptors. Other examples are sensors in the head for human visual, auditory, balance, gustatory and olfactory functions. There are also sensors in the skin for sensing temperature, pain and pressure. Sensors in joints records changes in joint position, speed of movement, position of the joint and pain sensation (Chen, 2004).

In addition to the sensation concept, the processes of human information processing also involve “bioelectrical neural codes” (Zadeh et al., 2010). For example, humans primarily notice a series of images when they watch television. Alternatively, humans can perceive the concept of an image series with regard to their past experience, memory or judgment with psychological processes. Psychological processes present visual occurrences in an expressive way. The concept of perception deals with these psychological processes including organization, interpretation and providing denotation to the output from the sense organs (Kassin, 2004; Zadeh et al., 2010).

Further discussion of perception is considered by Kassin (2004) who states that perception is an active, “constructive” process. Perception is simply defined by selection, organization and interpretation of sensory information activities. It is also explained as the transference of raw information from the senses as a “meaning” by the brain. A meaningful perception can be constructed with diverse concepts of perception as a whole in which sensations make up the sum of its parts. For example, a human being usually focuses on a figure before the background. Perceptual organization also defines a group characteristic into a perceptual concept based on the rules of proximity, similarity, continuity, closure and common fate. Another detail of the concept of perception is perceptual constancy. Sensory inputs are constantly changing while perceptual constancy maintains the stability of human perception. The concept of constant size also allows the human to restrain the understood size of different input through the retinal image through comprehension of spatial context. Shape constancy produces a perception that a human being will notice an object’s form as remaining the same even if its orientation modifies (Kassin, 2004).

Human perception is affected by several factors such as individual differences that include the ability of the human brain, the condition of human sense in question, the emotional state and sex. Other factors include cultural conditioning and training. Figure 2.11 shows factors affecting perception.

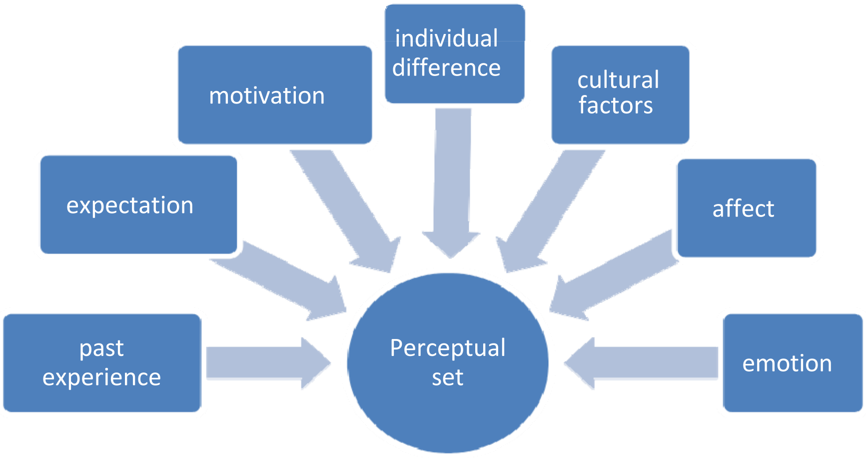


Figure 2.11 Factors affecting perception (Chen, 2004; Zadeh et al., 2010).

In conclusion on the concept of sensory and perception, its main purpose is to achieve precise and consistent information about the environment (Schiffman, 2000). A human can collect detailed information about the world and process the information to obtain a model of the real world through five senses of the human body.

The memory is a vital part of human information processing. There are numerous definitions of human memory. One widely accepted approach describes memory as a collection of the human systems and ability to encode, store, retain and recall the information based on personal experience, emotions, facts, procedures, skills and habits (Mastin, 2010; Hedge, 2011). Human memory systems have limited capacity and can be self-created. Anatomically, the human memory system is categorized into three subsystems: short-term sensory storage (STSS), working memory or short-term memory (STM) and long-term memory (LTM) (Mastin, 2010; Hedge, 2011). Figure 2.12 describes the hierarchy of human memory.

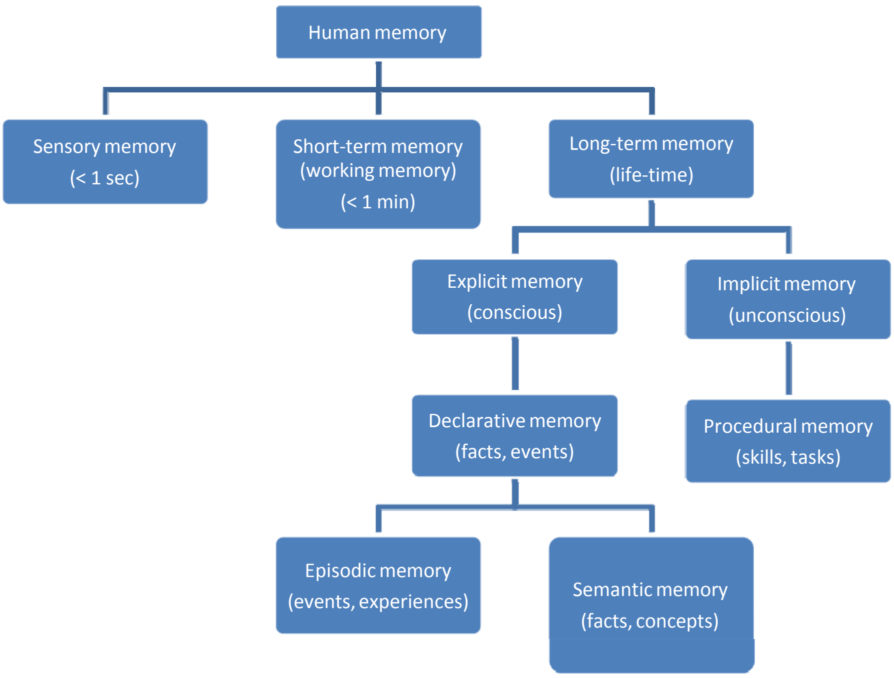


Figure 2.12 Categorization of the human memory (Mastin, 2010).

According to the concept of memory process that refers to a sequence of different stages rather than a unitary process (Mastin, 2010), the main process of memory is divided into four stages: encoding, consolidation, storage and recall (retrieval). Figure 2.13 shows the step by step process of human memory.

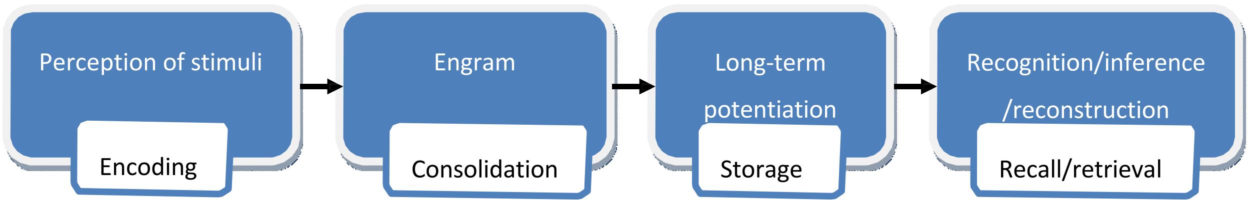


Figure 2.13 Process of human memory (Mastin, 2010).

Encoding is the first step of the memory process and begins with the perception of stimuli. It permits the senses to receive various new information to be combined with the existing information (consolidation process), and to be stored in the brain (storage process). The information can be recalled and reconstructed from long-term memory or short-term memory.

2.3.3 Human Cognitive System and Processes

A cognitive system is a system with the ability to view a problem in multiple ways and the ability to use the experience about itself and the environment. This means that the system has the ability to plan and modify its actions based on the above mentioned knowledge (Strube, 1998; Hollnagel and Woods, 1999). Modern cognitive psychology captures the basic characteristics of the cognitive system as processes, from reasoning to the planning and execution of action (Hommel et al., 2002). Besides adaptive and anticipatory characteristics, cognition also requires a sense of self-reflection (Vernon et al., 2007).

There are many positions on cognition. Each provides a significant different approach regarding the nature of cognition, what a cognitive system does and how a cognitive system should be analyzed and synthesized. Vernon et al. (2007) classify the interpretation of cognition into two views: the *cognitivist* approach, which is based on a symbolic information processing representation system; and the *emergent systems* approach, which embraces the connectionist systems, dynamic systems, and enactive systems that are based to a greater or lesser extent on the principles of self-organization.

Human mental models provide information on how to carry out tasks and what action should be taken if something unexpected happens. The mental model also provides information for problem solving when encountering unfamiliar systems. A point that should be considered when designing a work system is that the engineer's (or designer's) mental model is often not similar to the user's mental model. The cognitive model deals with the description and prediction of the user's problem solving behavior with interactive systems. This means that the cognitive models are utilized to construct and develop interactive systems (Chen, 2004).

By cognitive processes, the entirety of human mental functions is dedicated to information processing such as perception, attention, memory, problem solving and action as shown in Figure 2.14 (Stoessel et al., 2008).

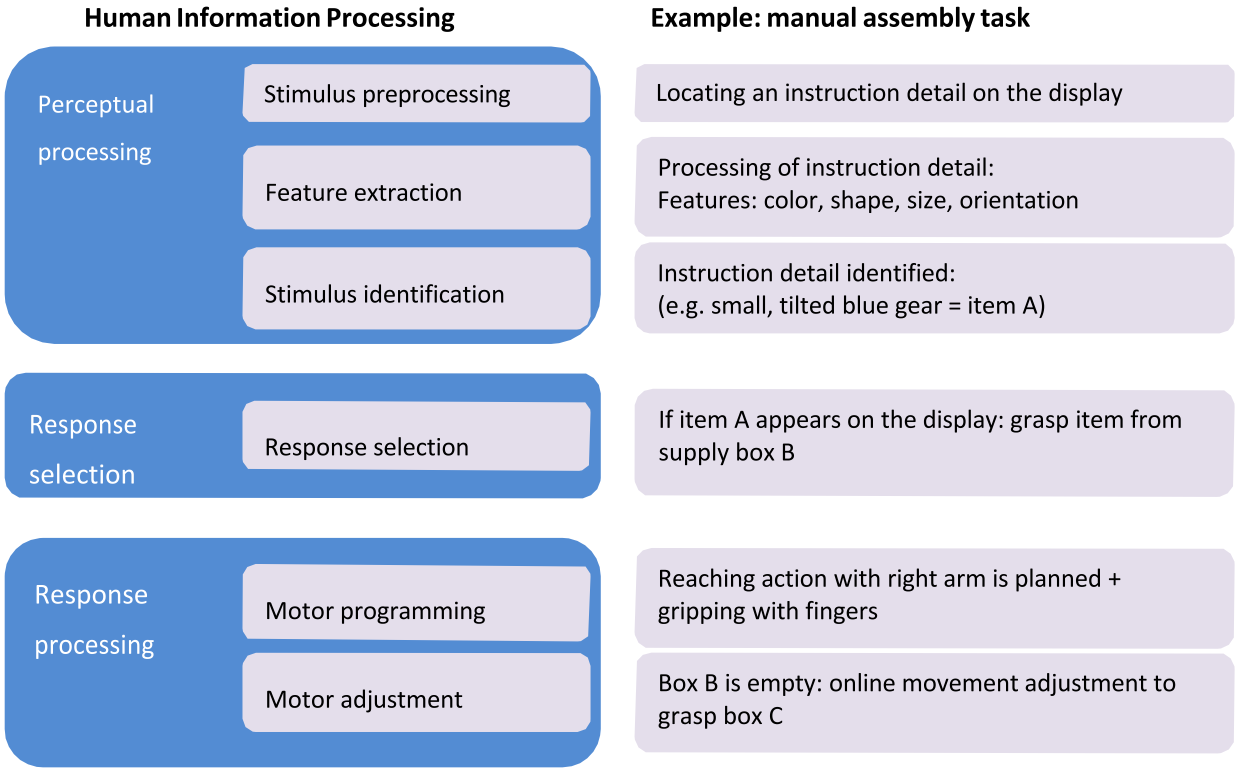


Figure 2.14 Left: Human Information processing stages (adapted from Sanders, 1990); Right: Mapping to corresponding processing stages within a manual assembly task (Stoessel et al., 2008).

An example of human information processing includes all actions that are performed in human working environment and described by the first identification of the stimuli. Processing and subsequently acting upon these stimuli are the next phase of cognitive processes (Schmitt et al., 2012). This phase of cognitive processes is adapted and deployed in Figure 2.15.

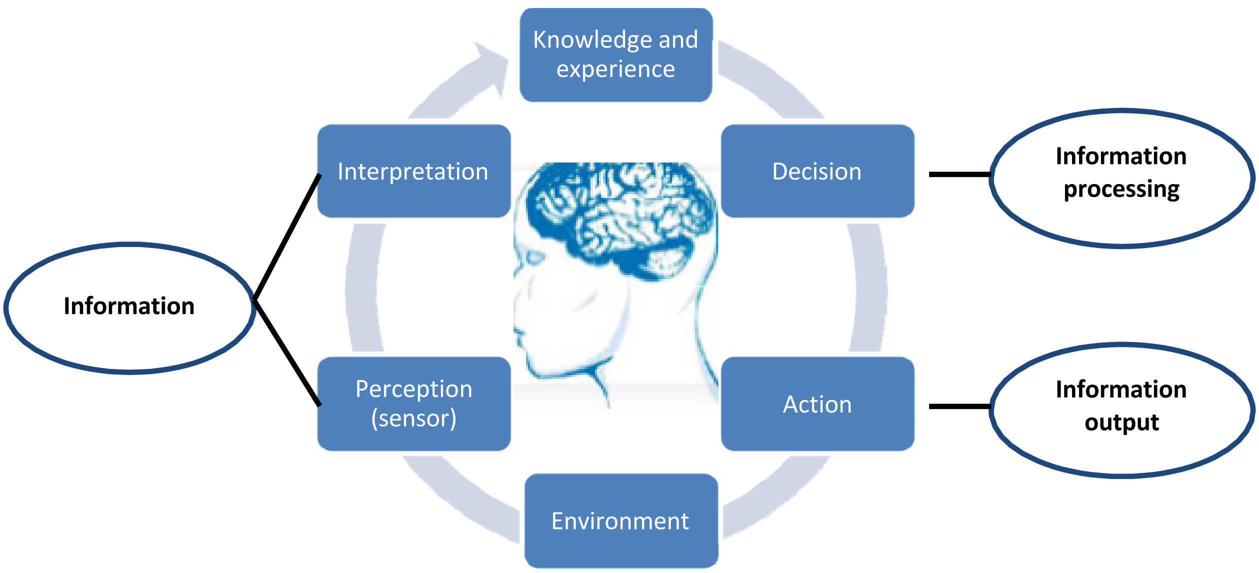


Figure 2.15 Model of cognitive processes (Schmitt et al., 2012).

2.4 Influence of Age and Culture on Human Cognition

2.4.1 Age-Related Differences

Decreasing performance level in different worker groups with regard to different age groups is an important point in a work system. For example, Pierson and Montoye (1958) show that the minimum reaction time and the maximum movement speed are achieved by individuals of 20 years of age.

A study concerning age group productivity is introduced by Yokomizo (1985). He investigates the influence of physical working ability of older workers based on the worker's age. The study employs the workability method. Based on simple motion observation it can be concluded that the physical ability deteriorates with ageing in the order of the upper arm, forearm, hand and fingers. Figure 2.16 shows the results of the measurements of the physical ability based on different age groups.

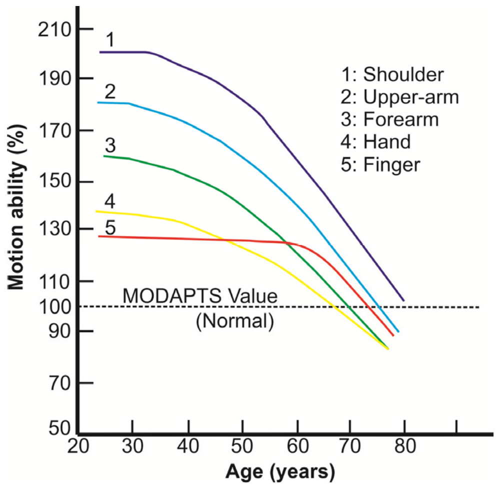


Figure 2.16 Simple motion measurement (reach, touch button, back, touch button) based on age groups (Yokomizo, 1985).

The measurements of elaborate motion show a similar result of the deterioration of physical ability as shown in Figure 2.17.

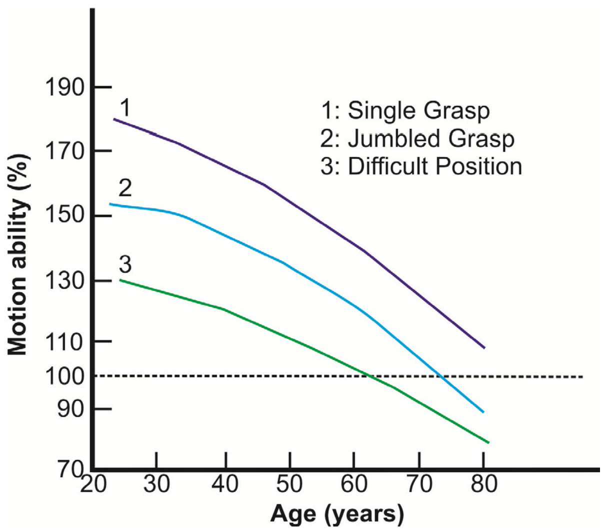


Figure 2.17 Measurement of elaborated motion (reach, group, move, put) based on age groups (Yokomizo, 1985).

It is claimed that deterioration of ability increases with people in their twenties to forties, decreases with people in their forties to sixties and increases again with people over 60 years of age (Yokomizo, 1985). Subsequently, performance level becomes less with increasing age. Similarly, subjects of an age greater than 60 years perform increasingly inharmonic movements and more frequently miscalculate distances (hypermetria indication) (Cooke et al., 1989).

Another recent study (Jochems, 2009) regards the influence of age in human-machine interactions for a case study in project management. It explains how different age groups influence visual acuity and performance in a detection task.

According to Göbel and Zwick (2011), the relationship between ageing and performance, especially in the area of medicine and psychology, depends on the analyzed performance dimension, such as physical performance and psychological performance. Virtual measurement of physical performance usually shows that performance results decrease with increasing age, while psychological performance show varying results of productivity measurement. Remarkably, a positive relationship is indicated in the psychological relationship between age and productivity. In conclusion, it can be said that a mixed relationship between age and performance is observed regarding occupation and profession. The diversity is also defined differently with regard to the skill, experience and knowledge of the worker. The difference is specified based on the industrial structure in economic sectors. Because industrial structures between countries are different on many levels and the service sector in most industrialized countries is becoming more and more important, the study of ageing and worker performance relationship is of high economic importance.

For a production system in the manufacturing sector, technology and production processes determine the degree of human worker knowledge and experience. For example, if production processes require a lot of specific knowledge from the human worker, a steep learning curve can be expected. A learning curve defines the necessity of using younger worker in the beginning of the setup of a work system. The manufacturing sector habitually requires more specific knowledge than the service sector. Thus, a younger worker is demanded to obtain a relatively higher productivity. Since an older worker takes less part in training than a younger worker, the relative productivity of older worker is reduced due to the necessity of advance training. However, if the production processes require planning and an experienced decision maker, then older workers should participate more in the particular system than younger workers.

In the manufacturing sector, the age productivity profile increases until 30-35 years and then decreases until 55-60 years. Workers older than 50 years are described as having a lower productivity than the reference group (Göbel and Zwick, 2011).

The decreasing physical performance of different worker groups is analyzed by Börner et al. (2012). They examine the influence of decreasing physical performance due to increasing age on the work process. The findings are confirmed based on the results of an experiment of tempo-basic functions. They state that older people manage better in planning tasks their younger counterparts. Additionally, an analysis of the adaptation process of the worker through individual differences and the experience of older people is also examined. The result of this study aims at better planning and task allocating based on the needs of the elderly people who work in the system with highly age-critical movements. The study shows that there is a difference between younger and older women in average completion time for assembly task. The results of this study state that the younger subjects are at least 12% faster than the older ones regarding the average completion time of an assembly task.

2.4.2 Culture-Related Differences

Individual differences regarding cultural analysis frequently become a relevant point in cognitive systems. Mann (1998) resumes that the decision making process under uncertainty is based on cultural differences. It is clarified that Westerners implement a probabilistic approach and construct reasonable calibrations in the assessment of outcomes. Easterners, on the other hand, have a tendency to implement a non-probabilistic approach and conduct the outcomes as either certain or uncertain. Other examples yield that Westerners are more comfortable with regard to the decision- making process than Easterners. Asian culture is suspected to have greater "fatalism" than European culture leading to different levels of confidence in decision making, procrastination and hyper- vigilance.

Triandis, (2000) defines the cultural distance between Westerners and Easterners as a wide value in cultural dimension difference. For example, the Human Development Index (HDI) – an annual publication from the United Nations – is the most used method in the analysis of cultural distances. In the HDI of 2008, Germany was ranked on position 23, while India was on position 132. These facts indicate that the differences of these two countries are based on well-being and child welfare (human development).

Cognitive differences with regard to the perceptual fields of Easterners and Westerners are also studied by Masuda and Nisbett (2001). Based on the experimental result, it is reported that there are differences in information processing between Eastern and Western populations. The experiment is conducted using a short film clip showing a fish in a tank. The result explains that Easterners tend to apply a more holistic approach than the analytic approach of Westerners who see the world as a composition of separate parts. This means that Easterners pay more attention to the background context than the focal objects as by Westerners.

How the level of cultural difference influences cognitive processes is explained by Nisbett and Norenzayan (2002). As a basic process, the cognitive process is first constructed when a child is born. The cognitive structure develops as a system that comprehends model-based categorization, inductive and deductive reasoning, and long-term memory. In addition to the basic process, there are at least three important possibilities in the structuring of human cognition through different culture: the differences of cognitive accessibility; the differences of problem selection in the cognitive process; and the differences in actual cultural innovation of complex cognitive structure out of the universal basic cognition. These differences lead to a different construction of human cognition due to the individual differences in human cognition.

Cultural differences in cognitive accessibility are a prospective process of human cognition. Cultural practices consist of promotion, providing differential expertise in cognitive strategy utilization or differential knowledge of area (Nisbett and Norenzayan, 2002). The result of this study indicates that the cognitive process might be similar, but the accessibility of the cognitive process for each human can be different dependent on their cultural backgrounds.

According to Nisbett and Norenzayan (2002), in their study about cognitive accessibility, Easterners tend to manage their environment with regard to similarities and in terms of relationships. They also create descriptions based on situational events and tend to be certain of knowledge-based reasoning. Westerners have a tendency to manage their environment with rule-based categories. They describe events directionally and tend to depend on formal and decontextualized reasoning. The hypotheses of the cognitive differences between Easterners and Westerners are summarized by Nisbett and Norenzayan (2002) as shown in Table 2.1.

Table 2.1 Results of the investigation of the cognitive processes of Westerners and Easterners (Nisbett and Norenzayan, 2002).

No	Cognitive aspect	Westerners	Easterners
1.	Attention to the field	less	more
2.	Relationship between the field and the object	less	more
3.	Notice relations among events	less accurate	more accurate
4.	Control in a normal situation	believe that they have more control, more performance improvement, increasing confidence	less confidence
5.	Explaining the behavior objects	presumed properties of the object itself	interaction of the object with the field
6.	Fundamental attribution error	more susceptible	less susceptible
7.	Complexity in the world	less potential causal factors at work	more potential causal factors at work
8.	Organization of the world	based on categorization and more rules covering	based on similarity and relationship, less rule covering
9.	Perception of content and structure	better ability to decontextualize	worse ability to decontextualize
10.	Argument validity	more accurate	less accurate
11.	Reaction due to apparent contradictions	resolve the situation by deciding which of the two propositions is correct (emphasize non-contradiction)	resolve the situation by find some truth in both propositions (value the middle way)

The above comparisons indicate that Westerners are cognitively different from Easterners based on their cognitive processes and conditions.

The experiment by Kitayama et al. (2003) investigates cultural differences through the Extent Framed- Line Test (EFT). This test divides tasks into two types of tasks: an absolute tasks (comparing a vertical line in a square frame with a new one that has the same length but smaller or bigger or similar size of square) and a relative task (comparing a vertical line in a square frame with a new one that has both smaller vertical lines and square with a constant reduction in proportion). The result of Kitayama's experiment shows that Easterners are more competent than Westerners in the relative task, whereas Westerners obtain a higher score than Easterners in the absolute task. It can be concluded that the visual perception of Easterners is more holistic than Westerners. It is also presumed that instead of considering perception of a single stimulus, Easterners tend to respond to the stimulus of the visual field as a whole system.

A recent study about cultural differences identifies many approaches towards experience that influence human perception (Kassin, 2004). Tipandjan (2010) describes that Germans (as the

Westerners) and Indians (as the Easterners) have different approaches to achieve their results. For instance, he explains that the Western culture is recognized as achievement-oriented and not as stimulation-oriented. On the other hand, the Easterners have a tendency of being strongly tradition-oriented.

Focusing on manufacturing systems, cultural differences become apparent with the necessity of cooperation with other international companies. For example, Gautam and Blessing (2007) investigate the influence of differences in culture between German (as Westerners) and India and China (as Easterners) on the design process. The result shows that there is a difference between the "Western method" and "Asian-Confucianist method" as seen in Figures 2.18.

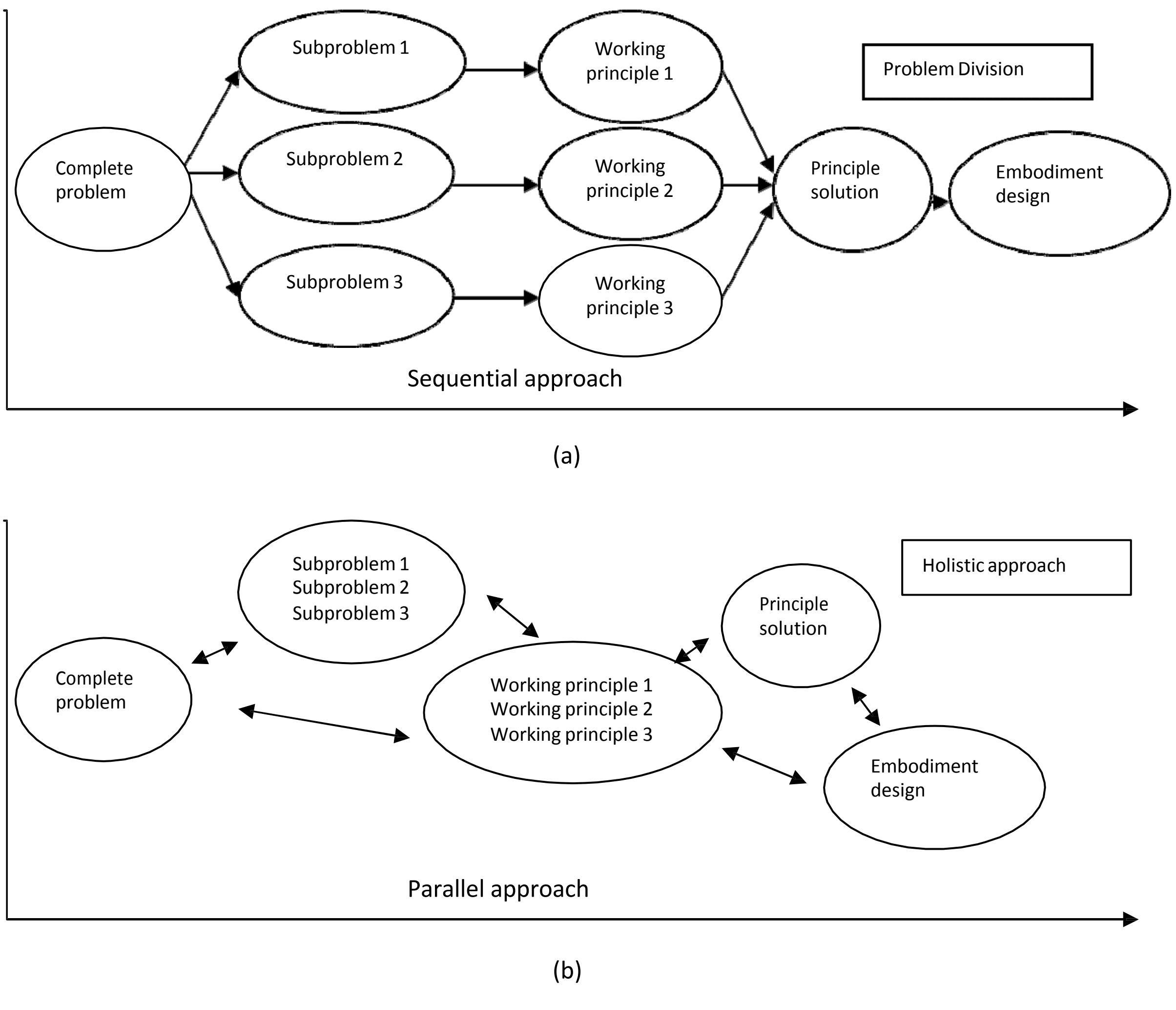


Figure 2.18 Differences in approach to problem solving between the Western method (a) and the Asian method (b) (Gautam and Blessing, 2007)

A specific study of cultural differences between Chinese and German subjects in assembly strategy is investigated by Sun (2010). Within this study, three aspects of assembly behavior are formulated. They are holistic versus analytic assembly, vertical versus horizontal assembly and writing or reading oriented assembly behavior. As a result, German subjects as Westerners adopt the analytic way by assembling the model layer by layer with a potential segregation process. In contrast, Chinese subjects as Easterners tend to work in a holistic manner and perceive the target model as a whole by using conditioning type and multi-layer assembly.

2.5 Human Cognitive Control

The investigation of human cognitive control cannot be separated from its history. It is needed to understand and provide a basis for the development of the application of cognitive systems. The first study about human cognitive control was performed by James (1890). Cognitive issues are defined and examined as the expression of personal goals and interests that are attributed to two dominating faculties: attention and will. Attention ensures the selection and processing of a goal-related environmental event, whereas will is responsible for the organization of element movement to achieve the intended goal (Hommel et al., 2002). Most studies highlight the characterization of the existent results of attention and will, such as the increase in clearness of objects or the experience of liability for self-intended actions. The processing aspect was not further studied in the late 1800s/early 1900s). Other studies as reviewed in Hommel et al. (2002) investigate many new empirical researches to examine the interaction and conflict between habits and the intentional processes. Recently, studies in the area of cognitive psychology shift their attention towards goals and influences on information processing and neglect this area to motivational and occupational psychology.

Hommel et al. (2002) identify the renaissance of cognitive control in the works of Atkinson and Shiffrin (1968) and Shiffrin and Schneider (1977), who re-introduce the distinction between automatic and control(led) processes (Ach's habits and intentional processes) to psychological theory. The term "attention" (as another semantic word for "will") comes into usage to illustrate the outcome of the process and the cause of it. This concept combines the terms "controlled" and "controller". Recent studies try to specify and focus on either the cause of control or the modeling cause of its control.

A cognitive control function is conceived as an emergent asset and should not be reflected as a basic mental function. There are two dimensions that interact or participate in cognitively controlled production. The first dimension includes the internal factor (such as goal-related attention control setting) and the external factor (such as prominent stimulus event). This first dimension influences visual attention as well as the control of response selection and dual-task performance. In the second dimension, a control is defined as an interaction of perceptual and response-related selection processes. Both dimensions show that a cognitive control, rather than being seen as a basic mental function supported by the neural circuit, can be considered as having "emergent properties" (Hommel et al., 2002).

A notable feature of the human cognitive system is the ability to develop itself for the completion of specific tasks with appropriate adjustments of perceptual selection, response biasing and the online maintenance of contextual information. The adaptability of the process is referred to as a cognitive control (Botvinick et al., 2001).

A cognitive control solves conflicts between the appropriate and the inappropriate response tendencies and denotes both the control system and the information processing in the human brain. Schlagheken et al. (2011) analyze the process of problem solving using a unitary all-purpose conflict control system or independent subsystems due to different aspects of conflicting information. The result shows that the cognitive control of response conflicts operates in an accurately domain-specific manner. In addition, a different source of conflict does not reflect the domain-general cognitive control. Nevertheless, it shows the difficulty of response reactivation.

The current state of research on cognitive systems focuses on the application of human cognitive control into technical systems. The alteration of cognitive study encourages the change of destination of cognitive systems from the conservative psychology into a technical system.

2.6 Representation of Cognitive Control in Technical Systems

Cognitive systems are systems that integrate psychological data, human thought, and human process information. They are constructed to connect the intrinsic functions of human cognition and to increase human cognitive capabilities. Human cognitive control can be applied in a production system based on its representation and model. There are several models of human cognitive control in technical systems such as the development of the concept of cognitive production systems, cognitive architectures, cognitive computer systems and cognitive technical systems.

2.6.1 Production Systems in Cognitive Psychology

Production systems in the psychological study were introduced by Newell and Simon in 1972 with their research on human problem solving (Young, 2001). Young (2001) states that a cognitive production system is a cognitive processing model that contains a collection of production rules. A production system consists of the compilation of "if-then" rules that compose a model of information-processing for cognitive tasks. Each rule has two sections, a condition part and an action part. The procedure of the rule is defined as follows: if the condition is satisfied, then the action is applied. A production system is developed if new information can be added or deleted without any prior knowledge or warning about these changes.

The architecture of a production system consists of two memories: the production memory and the data memory. The production memory accommodates the rules while the data memory comprises the dynamic information about the task. The production memory is referred to as long-term memory, whereas the data memory is referred to as short-term memory.

Another relevant characteristic of conventional models is that the control module has no specific status in the model. Regarding the homunculus problem, the cognitive system can decide on the need for control through monitoring for conflicts in information processing that occur, for instance, when a stimulus confronts two competing response tendencies (Botvinick et al., 2001).

2.6.2 Cognitive Architecture

The cognitive representation of a robotic system can affect the intended human-robot interaction. Cognitive support is often needed to control this interaction. Cognitive architectures are created to simulate human cognition in multiple task situations (Newell, 1990). In a cognitive architecture, structures and functions that are required for human cognitive processes are managed (Grant, 1996). A cognitive architecture is designed to describe the primary representations and systems of human cognition. Taatgen and Anderson (2009) state that a cognitive architecture concept is used to transmit the broad theory of human cognition based on empirical studies on human cognition data and implemented with a computer program (Byrne, 2003).

A cognitive architecture can be defined in two ways. First, it can be described as a fixed set of mechanisms and structures that processes content to produce behavior. The second definition is taken from a theoretical point of view focusing on what cognitive behaviors have in common (Lehman et al., 2006). A human cognitive architecture by Sweller (2008) is defined as the method of human cognitive organization.

Since cognitive architectures embody the fixed part of human cognition, they cannot complete tasks and decision-making process. Thus, it requires knowledge to perform any given task. Cognitive models deal with the combination of a fixed cognitive architecture and a particular knowledge set. In the cognitive system, the knowledge combined with the model is normally introduced by the human designer, although there is an improvement of machine utilization to intensify and adjust this knowledge. The design of a cognitive architecture contains its representational assumptions, its memories characteristic, and operation of those memories (Vernon et al., 2007).

One popular cognitive architecture for simulating human cognition is Soar (Laird, 2012). Soar's basic architecture distinguishes between two memories: long-term memory (production memory and preference memory), represented by production rules and a set of logical "if-then" conditional statements, and working memory. The latter represents a Soar agent's current perceptions, beliefs, goals, intentions, and actions in the form of object-attribute-value symbolic representations. All tasks in Soar are formulated as attempts to achieve goals. To bring the system closer to its goal, Soar implements a decision cycle in which actions of productions are repeatedly fired and retracted, until Soar reaches what is called "quiescence," a state where no more changes to the working memory are proposed. During the decision cycle, all productions that match the current state fire in parallel, whereas any potential conflicts are resolved by additional elaboration rules of the preference memory. Additionally, separate episodic and semantic memories have been added to the basic architecture as parts of the long-term memory. The episodic memory holds a history of previous states, while semantic memory contains previously known facts. If conflicts occur and the next operator cannot be determined or implemented, a so-called impasse will occur. Soar dynamically creates a new sub-goal to determine which symbolic operator should be selected or implemented. Soar includes a learning mechanism called "chunking", which can store new rules in production memory. Chunking occurs when results are produced in sub-goals. Once a chunk is added to procedural knowledge, it fires in new but similar way, avoiding the impasse that led to its formation. Reinforcement learning is also applicable to production memory by adjusting numeric values associated with rules. Episodic learning records the contents of working memory, while semantic learning stores individual elements of working memory for later retrieval. Applications for Soar are known in a wide variety of areas including the military domain, voice recognition and mobile robotics (Mayer et al., 2012).

2.6.3 Cognitive Computer System

The human cognitive function in a technical system is also investigated by Brachman (2002). He defines a cognitive computer system as a system of human cognition representation. A cognitive computer system has the ability to persuade, learn from past experiences, enhance its performance with time, and react knowledgeably to things it has never been confronted with. The system is also able to clarify what it is doing and why it reacts in this manner. These abilities allow the system to identify potential challenges to accomplish a task or to recognize when there is new information available. Figure 2.19 shows human and computer interactions in a cognitive computer system.

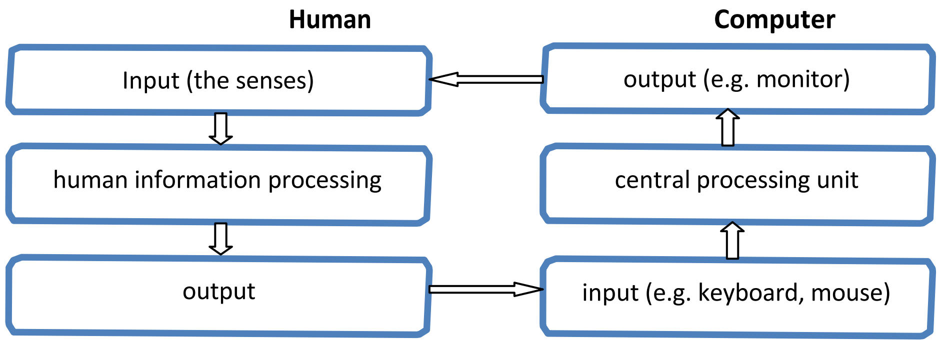


Figure 2.19 Cognitive computer system (Chen, 2004).

2.6.4 Steps in the Development of Cognitive Technical System

In the context of artificial systems, the cognitive technical system is an artificial system that elaborates cognitive skills. The cognitive technical system is able to adjust to different environmental alterations (Vernon et al., 2007). Onken and Schulte (2010) describe various cognitive systems for aviation and automotive control tasks using a system-ergonomic approach. An approach to human-centered automation in the field of aviation is discussed by Billings (1997). The interaction between a cognitive technical system for movement control and a human operator in the sense of a cooperative human-machine system is addressed by Flemisch et al. (2003), who introduce an interface-metaphor for cooperative vehicle automation. Biester (2008) investigates the driver-vehicle-interaction for such a cooperative system. Within the same application domain, Flemisch et al. (2014) describe cooperative guidance and control as a general concept for highly-automated vehicles and examine exemplary implementations.

Hauck et al. (2009) developed different steps towards endowing a cognitive technical system with higher-level capabilities as shown in Figure 2.20. The system starts with human-machine interaction where the cognitive processes occur only on the human side. The next step is an intermediate step that incorporates basic cognitive processes (such as reasoning, decision making and controlling) into the interaction system. The last step is a visionary cognitive technical system. This system incorporates cognitive processes on all levels, i.e. the human-machine interaction is based on multimodal communication. The human-machine interface adapts itself to the mental model of the human operator during the communication process.

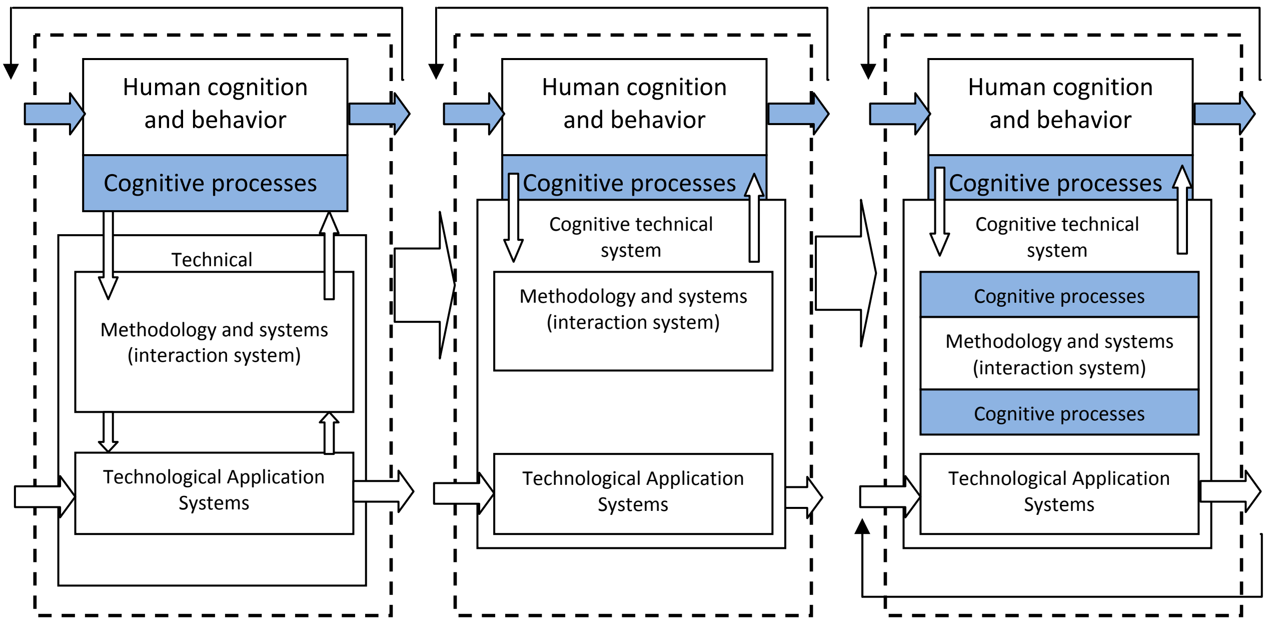


Figure 2.20 Steps in the development of a cognitive technical system (Hauck et al., 2009).

2.7 Cognitive Control in Self-Optimizing Assembly Systems

2.7.1 Self-Optimizing Assembly Systems

The concept of self-optimization has been continuously developed since it was initiated by Kalman in 1958 (Böcker et al., 2006). Applying the concept of self-optimization to the machining process not only enables the CCU to use strategies for automatic adaptations, it also gives it the ability to recognize environmental changes and fulfill control requirements in a changed environment.

Böcker et al. (2006) review three steps to execute and realize a self-optimizing control in Kalman's concept. The first step is measuring the dynamic characteristics of the system. The second step is specifying the desired characteristics of the controller. Finally, the third step is putting together a controller using standard elements that require dynamic characteristics. The controlled machine may repeat those three steps continually, notice and correct the system based on process characteristic changes. The machine can adapt itself to changes in its environment as termed by self-optimization.

At the Collaborative Research Centre 614 (SFB 614: Self-Optimizing Concepts and Structures in Mechanical Engineering) Böcker et al. (2006) used Kalman's concept to differentiate three steps: analysis of the current situation, determination of system behavior and adaptation of system behavior. The approach of the SFB 614, however, is not restricted to the control system, but is also appropriate for general technical systems. A self-optimizing system that is capable of an autonomous situation analysis, determining objectives, optimization, and behavior adjustment of the system, can therefore act autonomously in a very complicated environment (Böcker et al., 2006; Hauck et al., 2009).

Self-optimizing systems determine their current active purpose with regard to encountered influences. They react autonomously and adapt to changes in environmental conditions. They have to evaluate and improve their behavior during operation. Hence, the design of such systems is an interdisciplinary task. Mechanical, electrical, control, and software engineers are involved, as well as experts from mathematical optimization and artificial intelligence. The development of a self-optimizing concept is also applied to other fields such as machine control (Li and Horowitz, 1997), chemical machine design (Kassidas et al., 2000) and mechatronics (Böcker et al., 2006; Dumitrescu et al., 2009; Gausemeier and Kahl, 2010). Furthermore, self-optimizing systems adopt functions of the cognitive system. It is not necessary to change the early concept of technical self-optimizing to adapt to cognitive control system, but cognitive information processing should be able to co-exist with the technical system and analyze the current situation to adjust the system's behavior accordingly (Strube, 1998; Hauck et al., 2009).

Focusing on the assembly process as an important component of the production process of a company and the last value-adding process in a production system, Brecher et al. (2012) position the system based on the production polylemma, as can be seen in Figure 2.21.

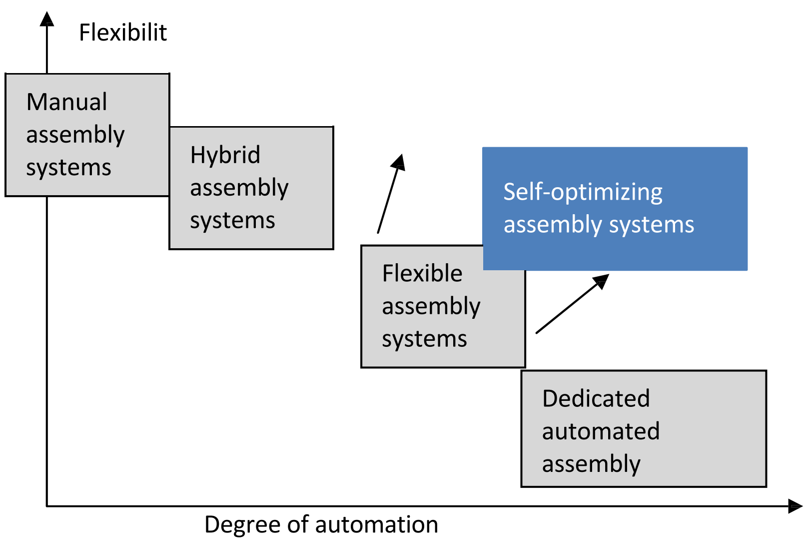


Figure 2.21 Classification of assembly systems (Brecher et al., 2012).

Schlick et al. (2014) defines a self-optimizing production system as a system that is able to carry out an endogenous adaptation of its objectives due to changing external objectives, operation points or operating conditions. Self-optimization also covers the resulting autonomous adjustment of the system state, control parameters or system structure and consequently the system's overall behavior. The objectives of self-optimization are efficiency, productivity, robustness, reliability, safety, flexibility, adaptability, reconfigurability (structure and processes), autonomy, development of skills, knowledge and abilities (human), transparency (human) and sustainability (environment).

Self-optimizing production systems are defined by the continuous execution of analysis of the current situation, determination of system objectives, and adaptation of the system structure or behavior to satisfy the new objectives (Schlick et al., 2014). This self-optimization cycle is started by defining the external objectives (of the human operator or other technical system). The analysis of the current situation is conducted by detecting both the influences of measurements and the system state, and by being able to process variable targets and limits, as well as identifying procedures and communicating with other systems. The next phase is the determination of system objectives based on recorded influences, assessment of the degree of fulfillment of external, inherent and internal objectives, and the evaluation of joint objective functions based on all objectives. The adaptation of the system structure and behavior is then performed and the cycle can be repeated from the beginning.

An extended architecture for self-optimizing production systems is shown in Figure 2.22 (Faber et al., 2013a; Schlick et al., 2014). It is a self-similar architecture comparable to the works of Litoiu et al. (2005) but adapted by Mayer (2012) and Schlick et al. (2014) to satisfy the requirement to reflect a socio-technical system. The system model, which can be considered as a hierarchic self-similar cybernetic model for cognitive automated systems, is a synthesis of different concepts: the generic joint cognitive system model and the Extended Control Model (ECOM) after Hollnagel and Woods (2005); the work system model according to Schlick et al. (2010); and the models of supervisory control after Sheridan (1992). The architecture covers the basic level of machine control and higher levels of controlling a cell or the whole shop floor of a company. Each level consists of a cognitive controller that embodies a control circuit. Thereby, the model builder creates the necessary models to make decisions and optimize the actions. As a result, each level has a predictive model of the interacting subsystems, which is the basis for the optimizer and decision unit. According to the work system model, the operator is introduced on each level of the production system. Thus, his/her main task is to interact with the cognitive controller in terms of performing monitoring and controlling tasks. The interaction between the operator and the cognitive controller has to be designed carefully in order to establish an effective collaboration. The overall system is influenced by the specified external objectives. They have to be aligned with the internal objectives in order to make the best decisions (Faber et al., 2013a).

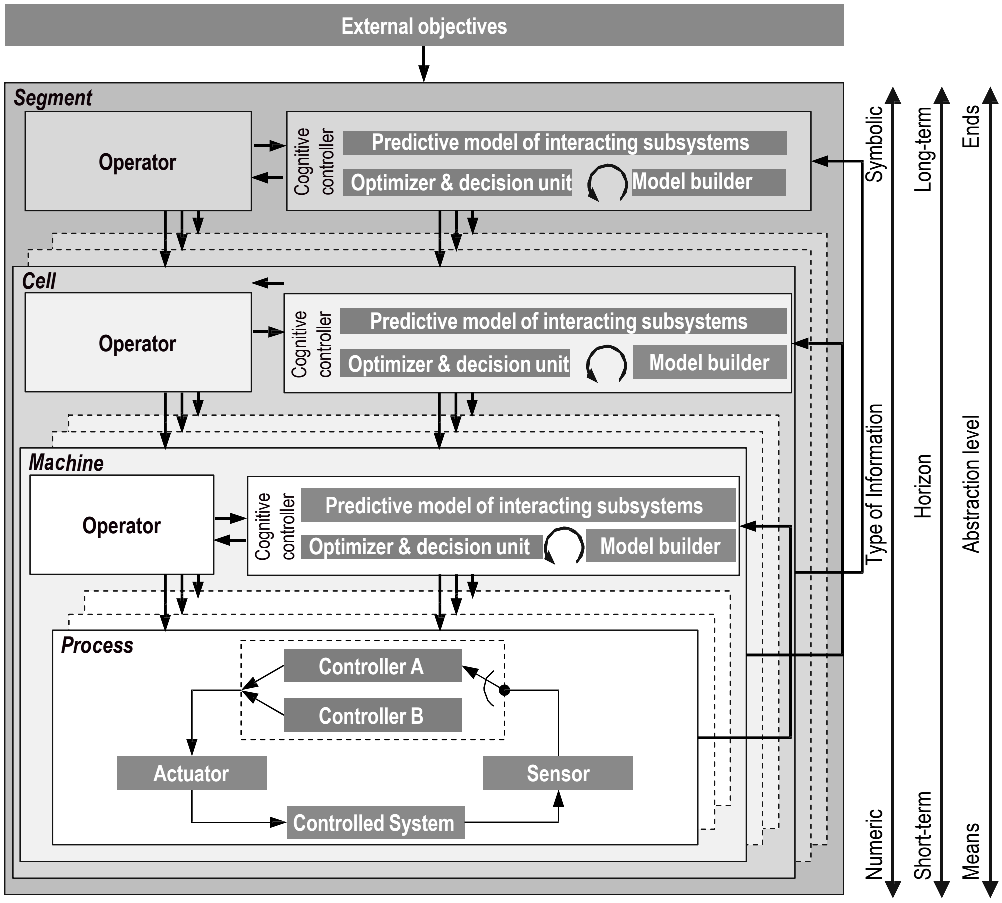


Figure 2.22 Extended architecture of self-optimizing production systems (Schlick et al., 2014).

2.7.2 Cognitive Control in Self-Optimizing Systems

An approach to develop cognitive control functions in self-optimizing systems can be found in Dumitrescu et al. (2009). The elaboration of human cognitive functions is highly abstract compared to descriptions of the natural cognitive functions: “to observe”, “to recognize”, “to map”, “to memorize”, “to think,” “to solve the problem”, “to control motor” and “to use language”. Table 2.2 summarizes the classification of cognitive functions for self-optimizing systems. This classification can be seen as a fundament for cognitive technical systems (Dumitrescu et al., 2009).

Table 2.2 Classification of cognitive functions regarding self-optimization (Dumitrescu et al., 2009).

Action of self-optimization	Cognitive functions
Analyzing the situation	“to observe”, “to recognize”, “to map”
Determining the system’s behavior	“to memorize”, “to think”, “to solve the problem”
Adapting the system’s behavior	“to control motor”, “to use language”

Separately, there are concepts of self-optimization developed by the Cluster of Excellence "Integrative Production Technology for High-Wage Countries" at RWTH Aachen University. This thesis focuses on the human-centered design of self-optimizing production systems. Thereby, the main objective is related to the need for an integrated view on production systems. The developed concept also refers to the optimization of conflict resolution without focusing too much on a single element. The design of self-optimizing systems can adapt to the objective based on the situation. Self-optimizing means that the system will work based on simulated cognition, which signifies that the technical system is able to perform planning (semi-)autonomously and learn from past experiences to a certain degree (Mayer et al., 2008). These systems are designed based on a continuous decision cycle: analyzing the current situation, deriving possible new system objectives, tasks and procedures and adopting the system behavior autonomously (Brecher, 2012). Thus, self-optimizing systems require a flexible and mutable automation. The automation should be able to manage complex processes without the necessity of manual intervention based on simulated cognition. The next generation of self-optimizing systems is able to learn and adapt their behavior. Regarding joint cognitive systems, the human operator must be considered as part of the production system. Since human behavior is much more unpredictable than a machine, the mutability of the system also has to cope with that challenge (Faber et al., 2013b).

Self-optimizing production systems aim at realizing value-oriented approaches with an increase in planning efficiency by reusing gained knowledge on new production conditions (Hauck et al., 2008). This concept is specifically developed to fulfill planning efficiency in the human role. The elaboration of self-optimizing system aims at simulating goal-directed human behavior and, therefore, significantly increases the conformity with the operator's expectations (Mayer et al., 2011).

The decision cycle of a self-optimizing production system is developed by Schlick et al. (2014) as shown in Figure 2.23. The control loop of an adaptive system not only monitors the target state of the externally prescribed target parameter, but simultaneously adjusts controller parameters to the observed change. A self-optimizing system adapts its own target system independently based on internal and autonomous decisions. It dynamically defines its own (new) target, derives the corresponding tasks and procedures independently, and tries to achieve the external objectives through the classical control and adjustment of controller parameters.

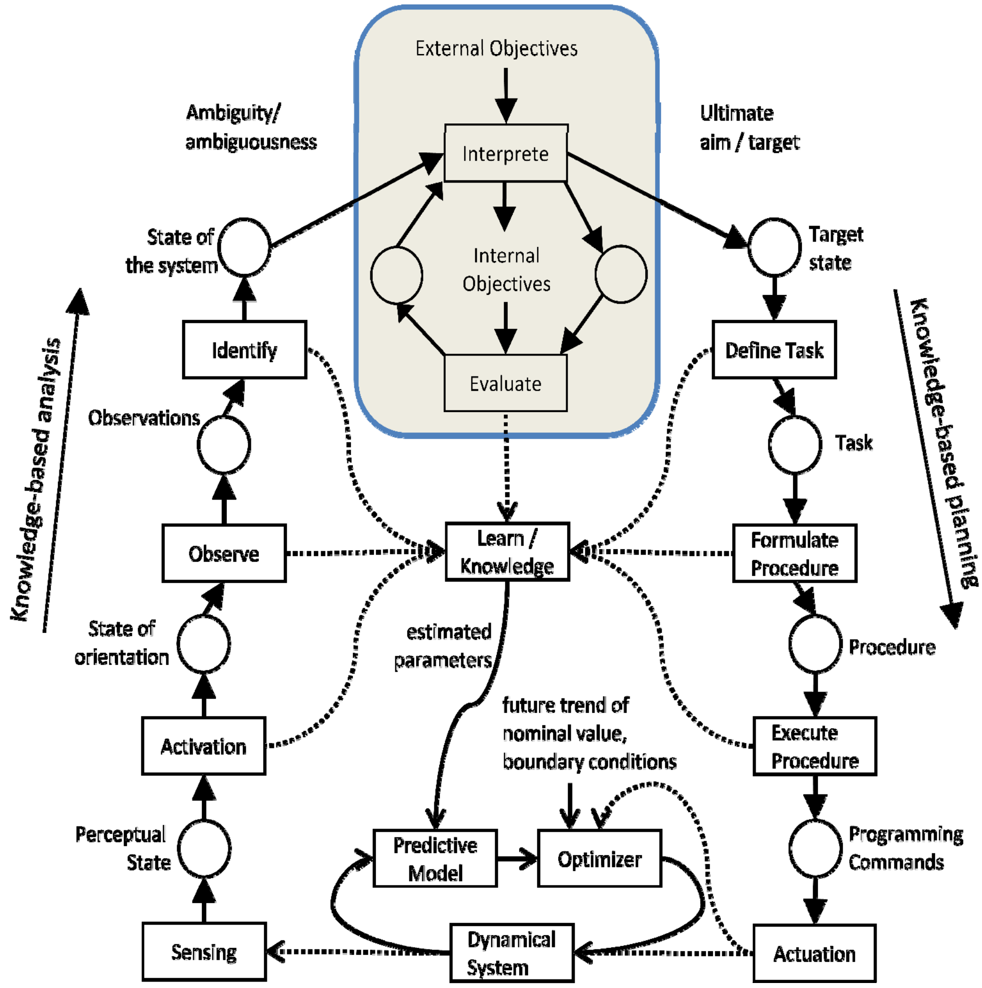


Figure 2.23 Decision cycle of self-optimizing production system (Schlick et al., 2014)

2.7.3 Cognitive Control Unit

Cognitive control refers to the cognitive control system and information processing in the human brain. This concept is transferred technically to a cognitive production system to obtain self-optimizing functionality.

Mayer et al. (2009; 2011) analyze HRI with respect to cognitive control using the cell's numerical control, which is termed as a cognitive control unit (CCU). The CCU is designed to model human information processing at the rule-based level of cognitive control. It is a human-like technical system to control the cognitive function of the production system. The framework is arranged around the cognitive agent platform Soar (Kempf et al., 2009). The task of the CCU is to plan and control the assembly of a product described exclusively by its computer-aided design (CAD) data. The accordant description is specified by a human operator, but afterwards the system plans and executes the assembly autonomously. During the actual assembly process, the CCU cooperates with human operators. While most of the assembly actions are executed by the assembly robot, certain tasks can only be accomplished by the operator. Based on these results and focusing on direct HRI, it can be stated that additional rules – taking human rule-based behavior into account – have to be integrated in the knowledge base of the system. The CCU can also react to changes in assembly processes and uncertain conditions due to increases product numbers and variations in production spaces.

The concept of cognitive automation based on human cognition simulation aims at solving the previously cited vicious circle problem (Onken and Schulte, 2010). Technical systems should not only be able to (semi-) autonomously carry out process planning, but also be able to adapt to alterations in manufacturing environments and learn from experience to a certain degree (Mayer et al., 2009). In other words, the technical system should also be able to simulate goal-directed human behavior. Therefore, there is a significant increase in technical system conformity with the operator's expectations (Mayer et al., 2011). Within this concept, knowledge-based behavior in the sense of Rasmussen (1986) (and also skill-based behavior to a significant extent) cannot be modeled and simulated. Hence, the experienced machining operator fulfills a key role as a capable problem solver in unstable and unpredictable situations (Mayer et al., 2011).

Supervisory control is the main human task in standard automated production that involves managing and monitoring the manufacturing system. In the case of malfunction, they must be able to take over manual control and return the system to a safe and productive state. The concept by Sheridan (2002) involves five typical subtasks: planning, teaching, monitoring, intervening and learning. This concept has been developed and matched with the cognitive control unit (Mayer et al., 2008). The classic scheme of Sheridan (2002) has been revised with taking the CCU into account. The human operator and the CCU take place on the task allocation in the revised scheme. The CCU is able to plan a given task autonomously according to the procedure and to implement the planning related to its knowledge-base included in the memory modules. Therefore, the task of planning and teaching are allocated to the cognitive system. Figure 2.24 depicts the task allocation between human and machine in a cognitive automated system.

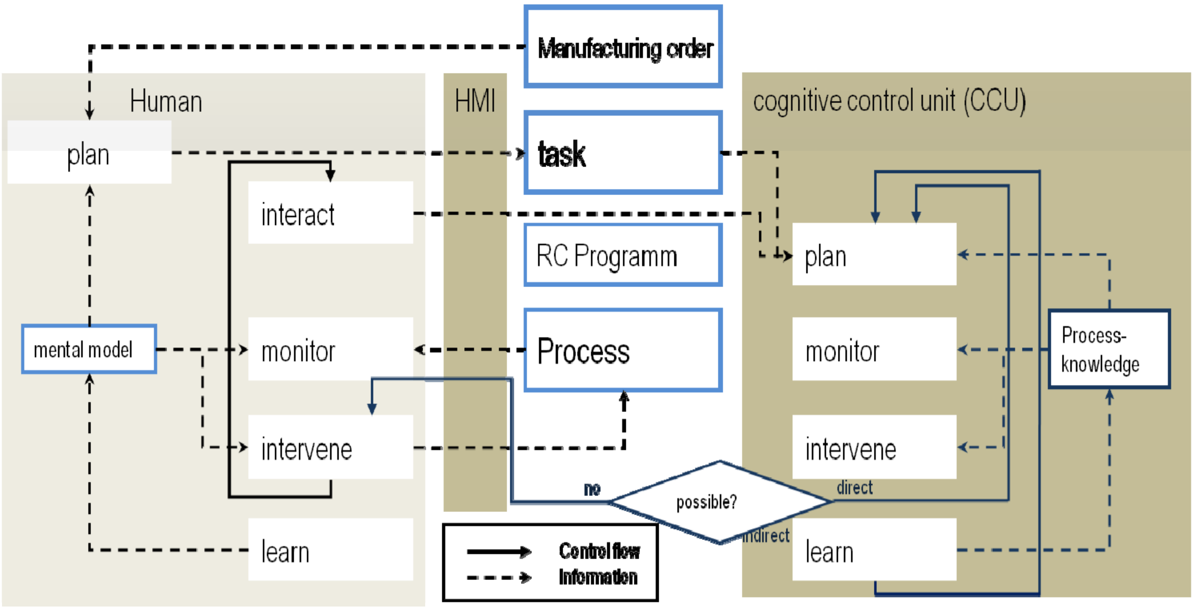


Figure 2.24 Extended supervisory control approach for cognitive systems (Mayer et al., 2008).

The main scenario and purpose of the CCU is to find a solution directly based on known production rules. If the rules in the knowledge base level cannot be applied directly to solve the problem, the problem will be decomposed into sub-problems that can be solved directly. In the future, the Soar system design may also make it possible to store whole solutions as a new rule in process knowledge to be applied the next time the problem arises. In the case that a solution can neither be found directly nor be found by decomposing the problem into sub-problems, the operator will step in as the problem solver to compensate for the lack of knowledge and transfer new information to the system. Otherwise, the system controls itself (Mayer et al., 2008).

The CCU is designed based on Soar (Mayer et al., 2012), a cognitive architecture, which was designed to simulate the human decision making process. Figure 2.25 shows the schematic sequence of the CCU. During the assembly task, the CCU analyses the current state of the system, then transfers it to the online planner and receives the assembly plan. Based on the system state information, the next action is taken by applying the stored rule base. The CCU can decide to follow the given assembly plan and to execute a suitable action from the first set of actions. Otherwise, it can decide to ask the human operator for assistance, or to wait until the situation changes, for example through a new component being fed in. After the action is executed, the resulting system state is inquired and evaluated. If the system achieves the target state, i.e. it contains the finished product, the assembly process ends (Buescher et al., 2012).

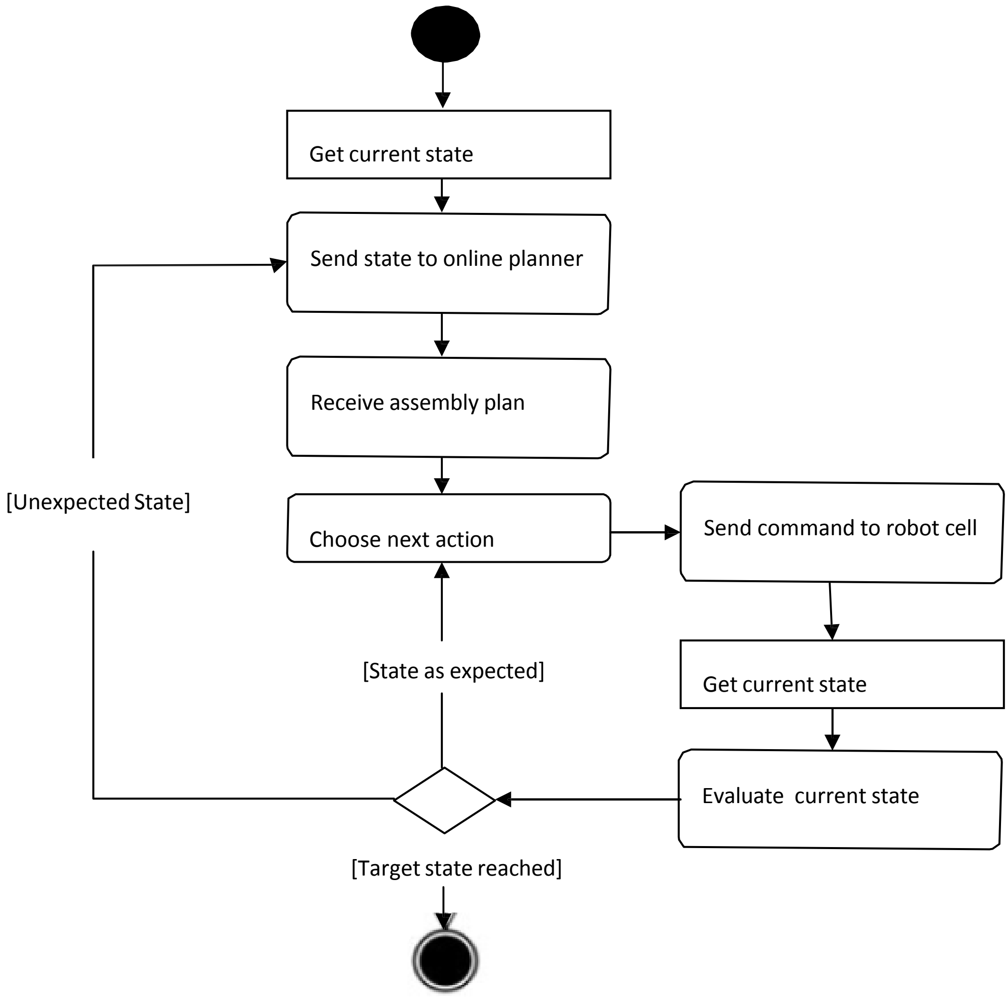


Figure 2.25 Sequence of information processing in the CCU (Buescher et al., 2012).

2.8 User-Centered Design

2.8.1 Concept

The term user-centered design (UCD) was introduced by Norman (1986). Norman (1988) advocates a design that prioritizes the needs of the product user in an early design phase. Design failures can cause human errors when using the technology in question. A good design considers the human capabilities involved to minimize user problems. A design process that focuses on psychological variables involves memory, strategies, mental models and the learning of the user.

Related to the human cognitive system, cognitive engineering (Rasmussen, 1986) can be considered a user-centered approach to designing complex technical systems for cognitive compatibility. It is especially appropriate for adaptive systems such as teams that consist of people and/or intelligent machine agents. Cognitive engineering is also an example of a user-centered design approach to the development of human-machine systems. This construction of system design considers an analysis of individual work task, teamwork, and collaborative work in problem solving and for the accomplishment of system goals. As a result, cognitive engineering has been promoted as a user-centered approach to system design with regard to support systems in user interface design that accommodate the system in work problem solving (Eggleston, 1998).

The development of UCD aims to clarify and integrate design practice and user research activity. The contribution of user-centered practices in design activity has enlarged the understanding of user’s needs. Sanders (2001) explains that the UCD is developed by a step-by- step support of user-centered practices in the design practice.

The general principle of UCD is that the user performs an integral role in the specification, design, development, and testing of the system. In the case of HRI, the designer should generally understand the needs and requirements of the targeted user group. This concept contributes to design-effective, efficient, usable, and deployable interfaces. An initial consideration in the UCD process is given to examining such needs (Adams, 2002).

UCD applications underline two attributes: collecting data directly from users and combining the results of data collection iteratively into product development. The result is a repeated process of designing and testing for usability. This process is expected to satisfy UCD goals: to fulfill the requirements of the product user and to minimize problems in product use (Nichols et al., 2008).

The most recent technologies are designed to help the human involved and to assist the completion of their tasks. However, most of them are designed based on engineer-centered approaches, which have no focus on the physical fatigue or the cognitive overload (or fatigue) of the user. This results in the user ceasing use of the device. To solve this problem, the engineer can first ask themselves whether the device is usable and easy to handle. This way of thinking leads to a user-centered designing approach as reflected by Rezazadeh et al., (2011), who proposes that:

- the main focus is on how to design a device in a way that is more suitable and comfortable for the user.
- the user's feeling regarding the device is more important than the applied technology within the design.

Rezazadeh et al. (2011) also suggest a number of methods for understanding the user's needs and ideas about the device during the usage period. This method uses questionnaires, physical performance factors (such as task completion time), achievement measurement during execution and affective measures for exploring the user's satisfaction.

2.8.2 Application in Human-Robot Interaction and Robotic Assembly Systems

Studies on HRI should be continued based on the work system development. With regard to the assembly task, Heiser et al. (2004) describe an approach for identifying design principles through experiments that examine the production, preference, and comprehension of assembly instructions for furniture. The results indicate that computer-integrated instructions informed by cognitive design principles significantly reduce assembly time on average by 35% and error by 50%. An effective design of visualizations is detected and validated through investigating production, preference and use of instruction in exploratory studies based on cognitive design principles for assembly instructions. Some procedures are constructed to expose the cognitive principles of effective instructions, and to apply those principles into algorithms for integrating individualized visual instructions on demand. The validation of the principle is performed by comparing the performance of users with the generated instructions from the factory. The outcome of the experiment indicates the effectiveness of instructions generated by an automated system that utilize an approach of identifying relevant design principles (Heiser et al., 2004).

The system should not only design a robot and its interaction with a human, but also consider the human’s workload, vigilance, and situational awareness (SA) (Adams, 2005). There are many studies about standard design with UCD principle. For example, one methodology elaborates on design for situational awareness (SA) with 50 design principles that are outlined and applied to various SA assessment techniques. They propose Goal-Directed Task Analysis (GDTA) for detecting the operator’s basic targets, major decisions, and SA requirements. These techniques are applied in the fields of aviation and the military (Adams, 2005).

The user can react in different ways when two robots with the same technology are employed. The experience can be completely different depending on the type of interaction system. Therefore, robot designers not only need to be capable of their traditional task of design visualization, but also in developing a solid comprehension of the fundamental issue in HRI (Kim et al., 2011).

In general, research on HRI can be categorized into two approaches: “robot-centered HRI” and “user-centered HRI” (Kim et al., 2011) (see Figure 2.26). The most popular recent studies on HRI concentrate on how robots could be made to recognize, understand, and react effectively in their given environment in order to interact well with humans. These studies can be categorized as robot-centered designs. The research of robot-centered interaction usually refers to the perspective of robot engineers.

On the other hand, the user-centered HRI approach concentrates on the responses and comprehensions of robot users. This concept also examines how they adapt their manner as a result of robot responses in understanding and accommodating humans. In other words, user-centered HRI research can be outlined as the study of human-robot interaction aimed at empowering robots as a human users’ assistant in accomplishing their preferred objectives and improving the quality of user experience. The research of the design of user-centered HRI focuses on the perception, behavior and attention in design to the problems of the user. This aspect can be divided into the three components, i.e., aesthetic contextuality, operational contextuality, and social contextuality. Corresponding to the user-centered approach, this research utilizes intuitive approaches that employ “look like”, “function”, and “role” prototypes, which users can sense, communicate with, and estimate (Kim et al., 2011).

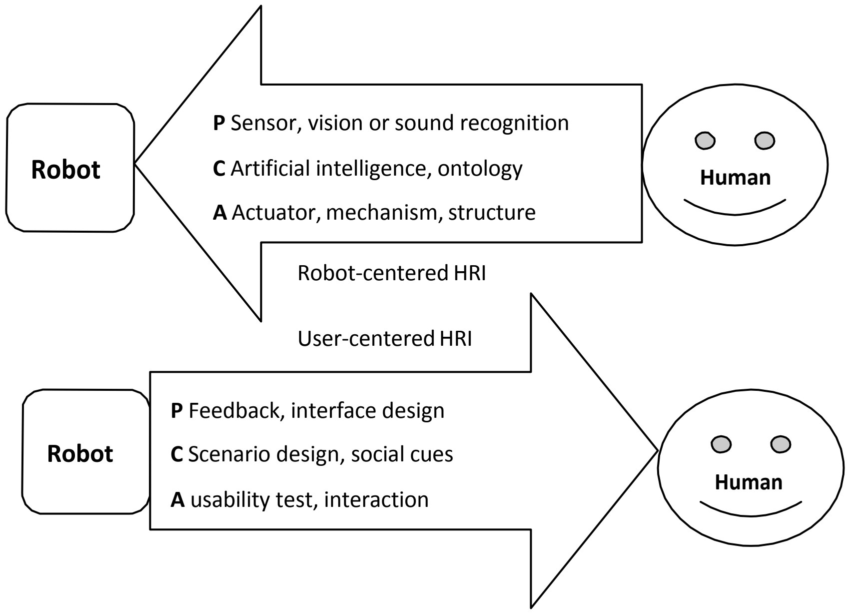


Figure 2.26 Dual approaches to HRI research: robot-centered HRI and user-centered HRI (Kim et al., 2011).

Within the scope of this thesis, the objective of UCD is to design the CCU of a self-optimizing robotic assembly cell for cognitive compatibility. Since the CCU can independently solve a certain class of rule-based production tasks, the human operator’s duties mainly lie in demanding cognitive tasks. The cognitive system in automation changes the role of the human operator (see Figure 2.10). The requirements of planning and teaching are decreased since these functions are performed by the CCU, but the interaction requirements are increased. The human operator still plays an important role in the production system regarding the necessity for detailed knowledge about the state of the machine and the process of decision making. The basic requirement for UCD related to the interaction between the human operator and the CCU system is the transparency of the system. The research question now is not about how to involve the human either continuously or continually, but how to provide the appropriate information to get the human operator informed and involved as fast as possible (Mayer et al., 2008).

A laboratory study based on an augmented vision system was carried out to examine the visualization utilized and to analyze how the relevant information should be displayed for the human operator (Odenthal et al., 2008). Technologies and methods of human-machine interaction (HMI) were developed by focusing on how to provide information in an individually suited way, according to knowledge, skills, abilities and preferred ways of learning. The research result shows that a head-mounted stereoscopic augmented vision system reduces the detection time of assembly error.

Another empirical study that considers compatibility between automation techniques and the mental models of human operators is conducted by Mayer (2012) with the identification of several assembly strategies based on human cognition. Kuz et al. (2012) introduce anthropomorphic movements in order to improve conformity with the expectations of the operator.

2.9 Implementation of a Cognitive Control Unit in Self-Optimizing Assembly Systems

2.9.1 Motion Description using the Methods-Time Measurement Taxonomy

Several studies have investigated the use of a motion descriptor for human behavior modeling in a broad spectrum of activities. In the technical field, one approach is the application of Fitts' law for the prediction of movement time in human-computer interfaces (MacKenzie, 1995). Another study was conducted by Weinland et al. (2006) using a novel motion descriptor based on the motion history volume (MHV). The MHV summarizes captured action in a short multi-view sequence without knowledge of the body parts involved to make segmenting and clustering sequences of volumetric reconstructions of a human operator without recognizing or tracking body parts.

The CCU transfers the partially non-value-adding planning and implementation tasks of the skilled worker to the cognitive technical system. Considering the matching process between process knowledge and the human mental model, it is essential to follow a human-centered approach in the cognitive automation system and develop a more familiar and easier way for the human operator to teach the system without the need for complex programming code (Mayer et al., 2008). The human operator has to understand the relevant CCU plans in order to supervise the robotic assembly cell. Therefore, a challenge is to design the knowledge base of the CCU to ensure conformity with the operator's expectations. Proprietary programming languages in conventional automation have to be learned as a specific domain and do not necessarily conform to the mental model of the human operator. To ensure conformity with the operator's expectations during the supervision of the assembly process (Mayer et al., 2008), the first step is to use the motion descriptors to plan and execute the assembly process, since motions are familiar to the human operator from manually performed assembly tasks (Gazzola et al., 2007).

The Methods-Time Measurement is a predetermined motion time system that is used to improve methods and establish time standards by recognizing, classifying, and describing the motions used or required to perform a given operation and assigning pre-determined time standards to these motions (MTM Association, 2014). The MTM-1 system is used as a library of fundamental movements in the design of the CCU. It is used for motion descriptors in the CCU to plan and execute robotic assembly. The sequences containing the validated basic movements are expected to increase conformity and learning process. The MTM-1 basic movements (REACH, GRASP, MOVE with integrated TURN, POSITION and RELEASE) are transformed into production rules and used to control the assembly robots. The further rules then are stored based on the basic elements used, the existence of the physical boundary, and the assessment of fed-in element state (Mayer et al., 2008).

The results achieved by Mayer et al. (2008) indicate that a motion descriptor based on the MTM-1 system is a good foundation for autonomous planning of an assembling task by the CCU. This MTM-1 system was further developed and mapped according to assembly rules from Mayer (2012). The obtained autonomous assembly planning system reverses as a reference model for simulation studies.

2.9.2 Human Assembly Strategies

Human behavior strategies in complex fields have been previously studied in Hornof and Halverson's experiment (2003). They describe eight different strategies of examining the way people search unlabeled and labeled layouts. Each strategy is encoded into the Executive Process Interactive Control (EPIC) (Meyer et al., 2001) that executes the strategy and generates predictions that are compared to the observed data. In their study, they assess the cognitive strategy using eye-tracking prediction when searching a hierarchical visual layout. Human strategies in robotized assembly are analyzed in detail by Birkhimer (2005) using “behavioral framework” methodologies to analyze human assembly data and to ascertain the nature of the human assembly strategies used. Stork et al. (2007) present an experimental setup to investigate the impact of different instruction modes on the first goal-directed movement during an assembly task.

Another study of human strategies in the work system involves Dennett’s three stances adaptation in three different strategies by Terada et al. (2009). This strategy consists of physical stance, design stance, and intentional stance. Each strategy is predictive. The subjects are asked to select the most suitable action sequence shown in three animations, each of which represented one of Dennett’s three stances.

Combining the human cognition support level and supervisory control, Fasth et al. (2009) develop a new model for manufacturing systems. Human cognitive support is divided into three separate levels as developed by Rasmussen (1983) which are: skill, rule and knowledge-based. A supervisory control model is developed and applied based on the human operator’s role: plan, teach (programming), monitor, intervene and learn. Table 2.3 shows the concept of the supervisory control roles that mix Sheridan’s operator roles and work task in the automatic assembly system.

Table 2.3 Operator’s role in assembly system (Fasth et al., 2009).

PLAN	Work instructions etc Long time planning (> 2 w) Short time planning (1-2
TEACH	Programming for a new product Material handling Order handling Set up
MONITOR	Manual assembling Monitoring machines Maintenance
INTERVENE	Disturbance handling Lack of material Small disturbances Large disturbances Quality check of product and system
LEARN	Continuous improvements Learning new working tasks Teaching new operators

2.9.3 Cognitive Compatible Development of a Cognitive Control Unit based on Human Assembly Strategies

With regard to the cognitive compatible development of the CCU for robotized assembly processes, Mayer et al. (2010; 2011) examine human assembly strategies. The CCU might have incompatibilities between the human's mental model and the process knowledge stored in the technical system. To avoid this, Mayer et al. (2010; 2011) study human assembly strategies and encode human behavior pattern in the form of production rules. The main purpose of this idea is to adapt the process knowledge stored in the CCU to the behavioral patterns. Another objective is influencing the behavior of the cognitive system in such a way that humans can easily understand and reliably anticipate it.

The Soar-MTM system is designed and evaluated in a simulation environment representing a self-optimizing robotic assembly cell (Kempf et al., 2009). Figure 2.27 describes the assembly cell prototype, while Figure 2.28 shows the assembly cells environment in detail.

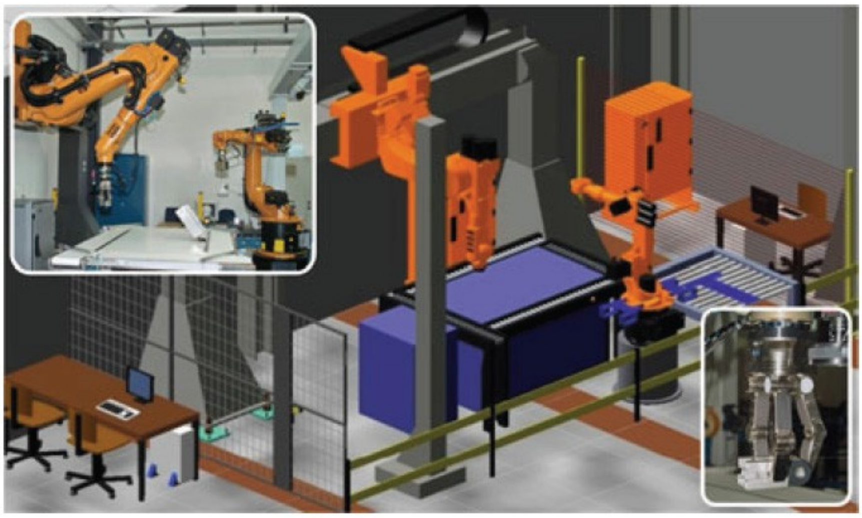


Figure 2.27 Design of prototypical assembly robotic cell (Kempf et al., 2009).

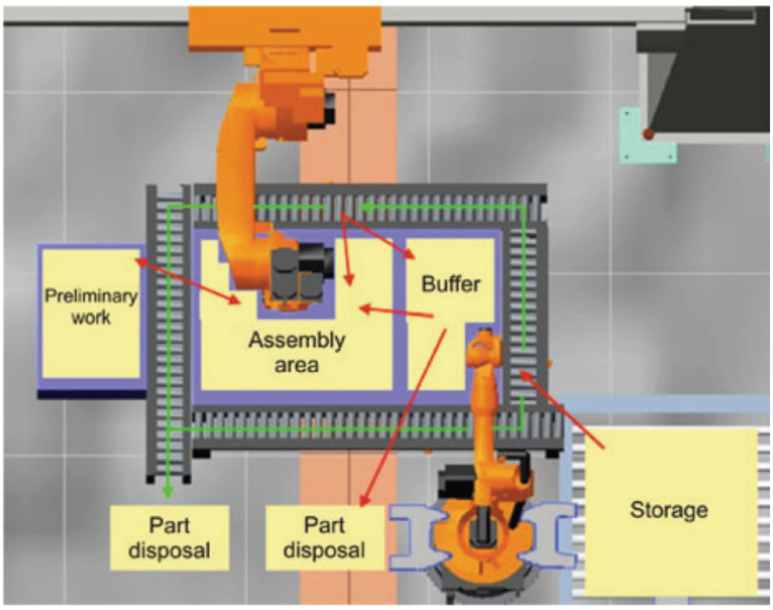


Figure 2.28 Assembly and storage areas in the assembly cell (Brecher et al., 2012).

The results lead to the design of the technical components in the human-robot system. This result shows that robotic assembly can be cognitively automated, but a hybrid approach considering the human being in the system has to be developed to maximize assembly feasibility.

A prototype implementation of the CCU in a simulation system is shown in Figure 2.29. A panel similar to a chessboard represents the conveyor belt. The fed-in bricks are positioned in the panel's fields. The workstation and the buffer areas are the independent areas.

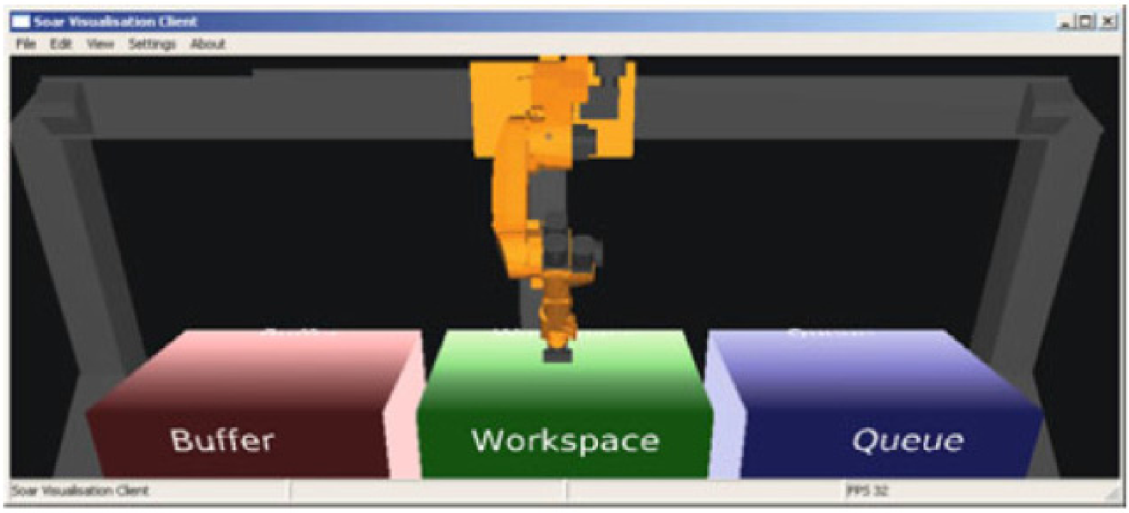


Figure 2.29 The simulation environment of the CCU prototype (Brecher et al., 2012).

To examine the effects of knowledge elaboration on conformity with the operator's expectation, a series of experiments was conducted under laboratory conditions (Mayer et al., 2009). The participants had to assemble a complete product consisting of LEGO bricks based on a CAD drawing. This experiment leads to three general production rules for assembly task:

1. The position of the first brick has to be on a left corner of the model.
2. If possible, a new brick is positioned as a neighbor to the existing brick.
3. The structure is built up in layers.

The next experiment is designed for evaluating the conformity of operator's expectation with the technical system based on prediction tasks. The predictability of human assembly behavior in evaluating the developed cognitive simulation models is formulated by Mayer et al. (2011). An empirical study is designed to compare the motion operations of a CCU with human behavior using different products. To improve the quality of the CCU inference compared to the human performance, the additional planning knowledge in the form of production rules has to be applied. Based on the results of the assembly tasks, the three production rules are added to the knowledge base (Mayer et al., 2009)

The predictive accuracy of a simulation model is determined by Mayer (2012) to examine the application of these three general rules. It is defined as the probability of the given brick to be correctly positioned by the simulation model. The overall predictive accuracy of the simulation model is calculated on the basis of the Logarithmic Conditional Probability (LCP). These results clearly show that minor additions to the CCU knowledge base can generate a significant improvement on the conformity between the assembly robot's behavior and the operator's expectations. Moreover, a predictive test for checking the cognitive compatibility of cognitive simulation models is also designed (Mayer, 2012).

2.9.4 Cognitive Simulation Model

The Cognitive Simulation Model (CSM) is designed to provide a simplified and compatible representation of the human's mental model in the production process (Faber et al., 2013b). This model aims at improving the transparency of assembly processes and therefore, the human operator is able to understand the system behavior.

The architecture of CSM involves the CCU as a core component. This CCU is primarily responsible in the planning of the section sequences and is based on the common three- layer architecture for robotic applications by Russel and Norvig (2003): planning, coordination and reactive layer. Figure 2.30 shows the architecture of CSM.

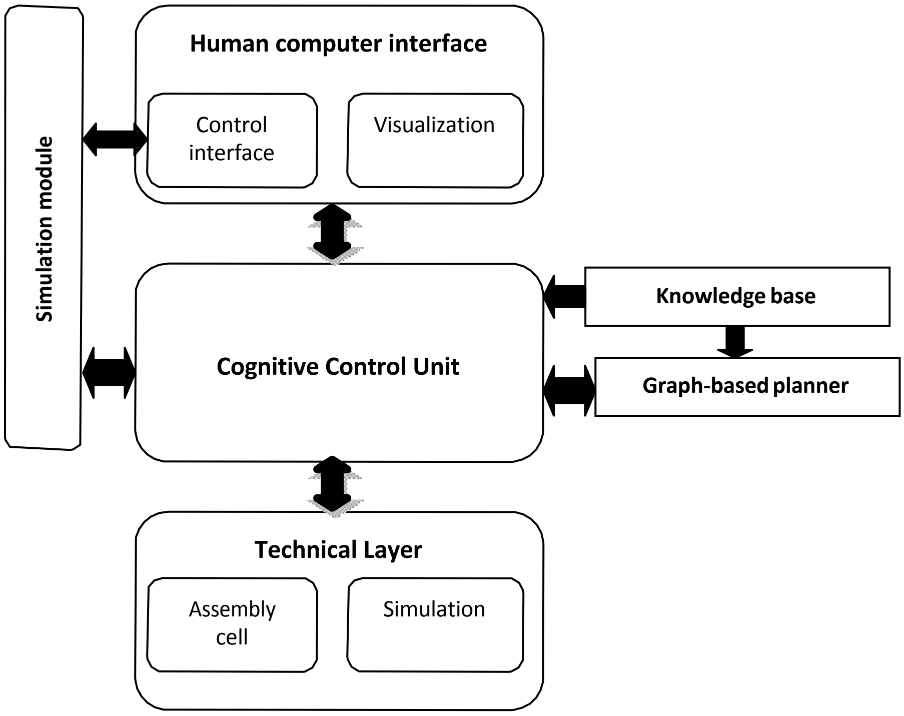


Figure 2.30 Architecture of the Cognitive Simulation Model (CSM) (Faber et al., 2013b).

The CSM is capable when applied in three different areas due to its flexibility. The first application is the usage as a comprehensive visualization of the assembly processes showing the current step of the robot and the assembly cell. The second application is the control of a real robotic assembly cell. The third application of the CSM is performing extensive simulations to evaluate different parameters or assembly strategies by decoupling the visualization and the control of assembly cells.

3. EMPIRICAL STUDIES

The studies concerning the user-centered design (UCD) of a cognitive control unit (CCU) for robotic assembly cells focus on the human-oriented design of the production rules incorporated into knowledge base of the CCU. Human-oriented design leads to an adaptation of robot behavior towards the human worker for assembly tasks. The more human-oriented production rules are incorporated into the knowledge base, the larger the compatibility between human and robot action to assemble the product becomes.

The studies can be divided into two empirical studies. Both empirical studies are conducted under laboratory conditions. The objective of the studies is to ensure that the CCU can execute robotized assembly processes in accordance with human capabilities and abilities. The intention is to find out how a human-centered CCU design can improve the conformity of human operator's expectations with robot behavior.

The objective of the first study is to replicate and validate Mayer's (2012) study results. The data replication is extended by elaborating the independent variables of the study. Independent variables in the first study include the model of robot behavior, the culture, the length of prior assembly sequences and the assembly groups. The main aim of the first study is to ensure that the identified human "cognitive patterns" in terms of activated production rules lead to the shortest prediction time of the assembly processes.

The second study focuses on the transferability of the human-oriented models from the product made from LEGO bricks into an actual manufactured product (in this study: a carburetor). The independent variables are also elaborated by considering the age of the person involved. The second study utilizes an eye-tracking system to obtain the areas of interest and acquire human gaze behavior data as well.

3.1 Study 1

3.1.1 Objective and Method

Study 1 aims to validate the findings of the previous study of Mayer (2012) by investigating different models of robot behavior concerning the prediction times in different assembly groups. Furthermore, the different cultural backgrounds of participants and different lengths of prior assembly sequences are investigated. The data is analyzed based on an ANOVA (Field, 2005) and evaluated in detail regarding the model of robot behavior and culture.

Apparatus

The assembly sequence of the robot is visualized on a 28" TFT screen. The assembly area is displayed in front of the participant. The completed assembly group is positioned slightly left of the screen. The assembly sequence, the corresponding assembly object, and the completed assembly group of objects are positioned in close proximity. The part to be used for the prediction of the next step is positioned on a table on the right. A video camera is utilized to record the position of the predicted part, while a light barrier is used to record information about the prediction time. Figure 3.1 shows the main component used.

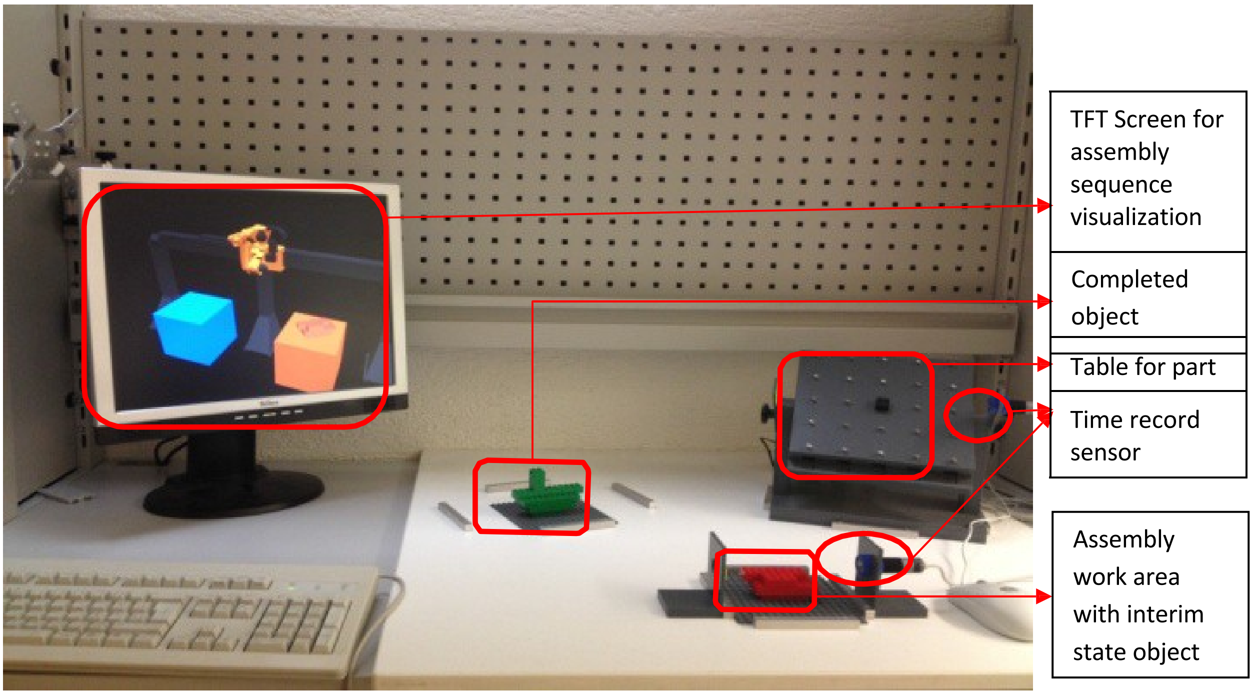


Figure 3.1 The environment of Study 1.

A virtual simulation is used to simulate the assembly sequence of the robot. The fed-in LEGO bricks are laid on the blue box. The orange box is the assembly work area. The robot then conducts the basic elements of MTM-1: REACH the brick in the blue box, GRASP the brick, MOVE the brick to the orange box and TURN the brick, POSITION the brick and RELEASE the brick. The robot only takes one brick up for each assembly sequence. The number and order of the assembly sequences change from trial to trial depending on the model of robot behavior and other independent variables.

Independent Variables

The study design distinguishes four independent variables. The four independent variables are the different models of robot behavior, the kinds of assembly groups, the length of prior assembly sequence and the different participants groups. The first and second independent variables were already investigated in the previous study. These independent variables are verified concerning their effects on the prediction time and combined with the other independent variables (length of prior assembly sequences and cultural background).

(1) Model of robot behavior for assembly (Models)

Based on the previous study by Mayer et al. (2011), Model 1 acts as the least human-oriented model in terms of the lowest number of human-oriented production rules (the so-called reference model). This basic model of robot behavior contains only the essential motion elements based on the popular Methods-time Measurement (MTM)-1 taxonomy. The human-oriented procedural knowledge about the assembly task is not included. However, this simulation model is capable of performing all possible physical assembly sequences. Model 2 represents a linear combination between the vicinity of the neighboring parts and the build-up of layer rules. Model 3 represents a combination of neighborhood and layer rules in a strong relationship, which allows only neighboring parts within layers. Model 4 represents the adoption of human assembly motion patterns in the assembly sequence. The assembly sequences are performed by a human operator and integrated into the knowledge base of the CCU being used in the study setup. In contrast to Model 1, Model 4 is designed as the most human-oriented model in terms of the highest number of human-oriented production rules. Model 4 is built on the basis of the findings of a small-scale study of human assembly behavior with three participants. They conducted the assembly of the completed object assembly group and interim states. An example for each model is shown in Figure 3.2.

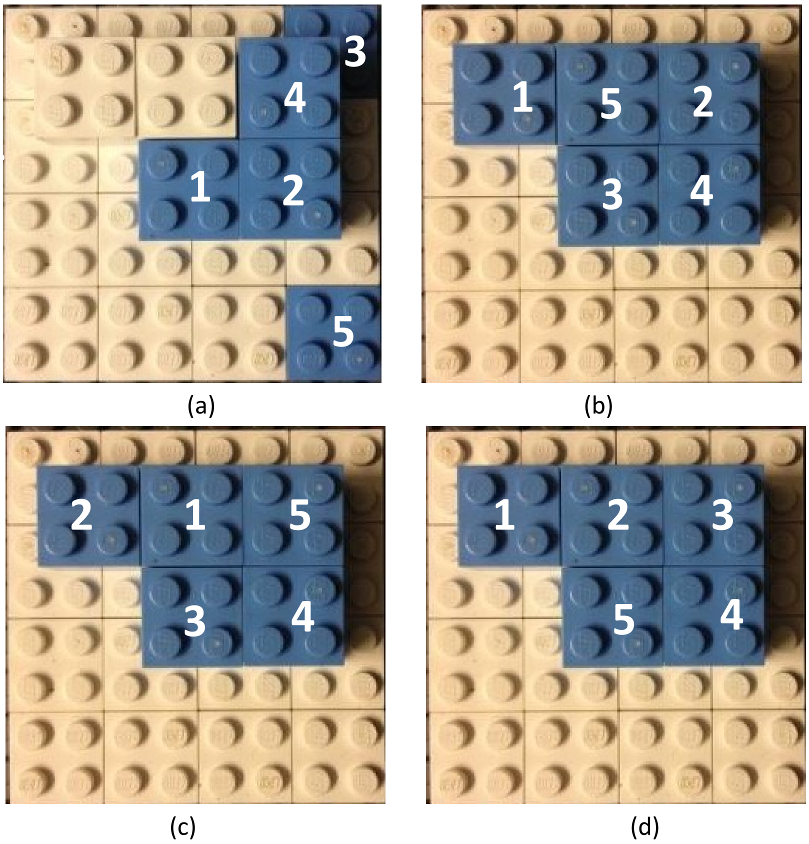


Figure 3.2 The assembly sequence of the product made from LEGO bricks based on Model 1 (a), Model 2 (b), Model 3 (c) and Model 4 (d).

(2) Kind of assembly groups

Three assembly groups are defined in this study for the robot to assemble. For every completed assembly group, there are two interim states to capture the robot and the sequence structure within human behaviors. The assembly group is determined based on the distinguished ability among the completed designs, as well as the similar number of possible positions of the performed brick based on Model 1 (see Figure 3.3).

(3) Length of prior assembly sequences (History)

The length of prior assembly sequences in Study 1 are five and seven bricks. The numbers of the five parts shown in the sequence history – known as Corsi Span – are chosen based on limits in human capacity of short-term memory due to visuo-spatial information processing in Corsi-block tapping tests (Corsi, 1972). A number of seven parts is selected as the representation of capacity of limit in working memory – known as magic number (7 ± 2) (Miller, 1956). It also selected as a variation from the above mentioned five-part example for a further examination of human limit capacity with regard to the increasing amount of assembly information.

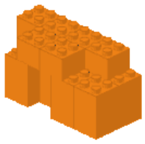
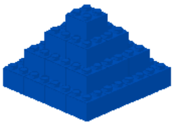
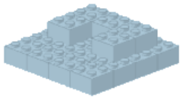
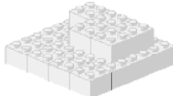
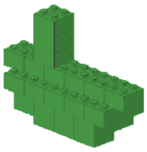
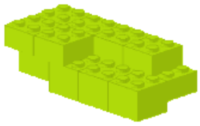
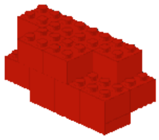
No	Assembly groups	Interim State	
1	House 	HO1 	HO2 
2	Pyramid 	PY1 	PY2 
3	Ship 	SH1 	SH2 

Figure 3.3 The Interim state and the completed assembly groups in Study 1.

(4) Participant groups (Culture)

Study 1 divides the participants into two groups based on their European and Asian cultural backgrounds. Each group represents the working culture of the respective region. The European group consists of German and Spanish participants, while Indonesian, Chinese and Indian participants represent the Asian group.

Summarizing the independent variables above, Table 3.1 systematically describes the independent variables related to the design of Study 1.

Table 3.1 The independent variables of the Study 1.

No	Variable	Variable levels
1	Models of robot behavior for assembly	• Model 1 (reference model, no human-oriented procedural knowledge) • Model 2 • Model 3 • Model 4 (maximum human-oriented procedural knowledge)
2	Length of prior assembly sequences	• 5 • 7
3	Kinds of the assembly groups	• Pyramid • House • Ship
4	Participant groups	• European • Asian

Dependent Variables

The dependent variables in this study are determined by the time required for performing a correct prediction (as an objective measure), task load, degree of dissatisfaction, and assembly strategy (as subjective evaluations). The prediction time is started when the participants finish the prediction task by putting the brick on the real interim state object once the robot has finished the simulation. A subjective evaluation is conducted by the participants for each prediction. The evaluation includes the determination of task load (0 = the lowest task load – 10 = the highest task load), the dissatisfaction grade (0 = the highest dissatisfaction grade – 10 = the lowest dissatisfaction grade) and the strategy recognition. The NASA-Task Load Index (NASA-TLX) method (Hart, 2006) is used to evaluate the task load and dissatisfaction grade of the participant during the assembly task. The same method is also applied to assess the assembly strategy.

Procedure

The procedure of study 1 is divided into two main phases:

(1) Collecting of personal data and training under study conditions

The first phase is the collection of relevant anonymized personal data (e.g., age, level of education and prior experience with the assembly task, as well as experience with LEGO assembly). After completing the personal data collection stage, the participant is introduced to the apparatus, the study environment that includes the interim state, and the completed object assembly group.

(2) Data acquisition

Next, the participant is shown a virtual simulation of an assembly task completed by a robot with the explanation about assembly sequence on the computer monitor. The participant is expected to recognize the robot’s work pattern in the sense of the assembly sequence of LEGO brick placement (see Figure 3.2). The participant must then predict the next brick placement using the real object after the robot simulations finish an interim state assembly. Afterwards, the participants give their subjective evaluation for each prediction task.

The prediction time is recorded and analyzed based on the independent variables for this study. There are 48 predictions conducted in four sessions (12 tasks each) with a random order of the robot behavior model and interim state. They take approximately 90 minutes for each participant to complete tasks including personal data collection.

Participants

There is a total number of 50 participants in study 1 (15 females and 35 males). The participant age ranges from 20-40 years of age. The participants grade their assembly experience with an average score of 2.3 (SD = 1.4), ranging from 1 (low) to 5 (high). The participants did not participate in the previous study by Mayer (2012). They also have no experience with the robotic assembly systems. Table 3.2 describes the participant specifications.

Table 3.2 The participant specifications in Study 1.

		Asian	Europe
1	Number of participants	25 (9 female, 16 male)	25 (6 female, 19 male)
2	Country of origin	Indonesia, China, India	Germany, Spain
3	Ages (years old)	28.2 ± 5.17	26.6 ± 3.43
4	Education level	High school - master	High school - PhD
5	Experience grade		
	- Assembly task	2.4 (range 1 – 5)	2.2 (range 1 – 5)
	- LEGO assembly	2.6 (range 1 – 5)	2.8 (range 1 – 5)

The tasks of the participants in this study are to predict the position of the next expected brick, to assess the task load and dissatisfaction grade, and to determine the strategy of assembly sequences.

Hypotheses

The following null hypotheses are formulated:

- The model of robot behavior (H_{01}), the assembly groups (H_{02}), length of prior assembly sequences (H_{03}), and the cultural background of participants (H_{04}) do not significantly influence the prediction time.
- The model of robot behavior (H_{05}), the assembly groups (H_{06}), length of prior assembly sequences (H_{07}), and the cultural background of participants (H_{08}) do not significantly influence the task load of participants.
- The model of robot behavior (H_{09}), the assembly groups (H_{10}), length of prior assembly sequences (H_{11}), and the cultural background of participants (H_{12}) do not significantly influence the dissatisfaction grade of participants.
- The model of robot behavior (H_{13}) and the cultural background of participants (H_{14}) do not significantly influence the subjective evaluation of the assembly strategy.

A Kolmogorov-Smirnov test is used to examine the normality of data, whereas a Levene's test is performed to test the homogeneity of variance (Field, 2005). An analysis of variance (ANOVA) is then used to test hypotheses H_{01}, H_{02}, H_{03}, H_{04}, H_{05}, H_{06}, H_{07}, H_{8}, H_{9}, H_{10}, H_{11} and H_{12}. The Cochran and McNemar test are used to test hypotheses H_{13} and H_{14}. The level of significance is set at $\alpha=0.05$ for all tests.

3.1.2 Results

Prediction Time

The test shows that the prediction time data is normally distributed ($p = 0.182$) and the variance is homogeneous ($p = 0.189$). Therefore, an ANOVA is conducted to investigate the main effects of the independent variables as a parametric test (Field, 2005). Table 3.3 shows the ANOVA results for the prediction time data. The *p*-values for the models of robot behavior and the assembly groups are less than 0.05 ($p \leq 0.001$). Therefore, both corresponding null hypotheses (H_{01} and H_{02}) are rejected. The *p*-values for the other variables and their interaction exceed the threshold 0.05 ($p = 0.456$ for culture and $p = 0.214$ for history). Thus, the corresponding null hypotheses (H_{03} and H_{04}) are not rejected.

Table 3.3. The ANOVA result for prediction time in Study 1.

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Culture	8492078.602	1	8492078.602	.557	.456
Model	3.456E8	3	1.152E8	7.558	.000*
History	23600476.682	1	23600476.682	1.548	.214
Assembly group	4.371E8	5	87414376.128	5.734	.000*
culture * Model	96954165.448	3	32318055.149	2.120	.096
culture * History	1042.802	1	1042.802	.000	.993
culture * Assembly group	36007188.113	5	7201437.623	.472	.797
Model * History	16933954.928	3	5644651.643	.370	.774
Model * Assembly group	3.024E8	15	20160581.986	1.323	.179
History * Assembly group	6182619.843	5	1236523.969	.081	.995
culture * Model * History	53315219.295	3	17771739.765	1.166	.321
culture * Model * Assembly group	2.112E8	15	14083024.854	.924	.537
culture * History * Assembly group	44425010.063	5	8885002.013	.583	.713
Model * History * Assembly group	1.090E8	15	7268984.926	.477	.953
culture * Model * History * Assembly group	1.630E8	15	10865156.143	.713	.774

*p < 0.05

- Model of Robot Behavior

According to the ANOVA results, the model of robot behavior leads to significant differences in the prediction time. The means of prediction time under different study conditions, including a 95% confidence interval, are shown in Figure 3.4. A post hoc comparison analysis with a Bonferroni correction for this variable is shown in Table 3.4.

Table 3.4 The post hoc test result for the model of robot behavior (Study 1).

	Model 1	**Model 2**	**Model 3**	**Model 4**
Model 1		1.000	1.000	.005*
Model 2	1.000		1.000	.000*
Model 3	1.000	1.000		.007*
Model 4	.005*	.000*	.007*	

* p < 0.05

According to the Bonferroni post hoc analysis (Table 3.4), the comparison between Model 2 and Model 3 has not shown a significant difference concerning the prediction time. This result suggests that the participants of the study cannot distinguish between the inherently different strategies of Model 2 and 3. Furthermore, there are no differences in the prediction time between Model 1 and Model 2 as well as between Model 1 and Model 3. However, the comparisons between Model 4 and the other models lead to significant differences in the prediction time. As depicted in Figure 3.4, Model 4, as the most human-oriented model, yields the shortest prediction time (mean 5334.215 ms, SD = 3761.30 ms), while Model 2 does exactly the opposite (mean 6357.122 ms, SD = 4329.879 ms).

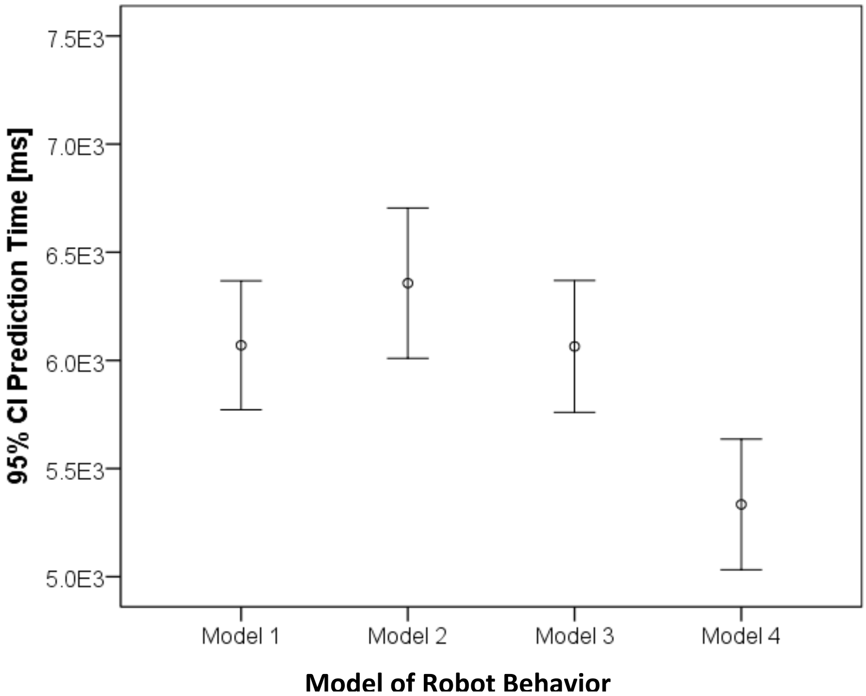


Figure 3.4 The error bar chart of prediction time for the four different models of robot behavior (Study 1).

- Cultural Differences

The ANOVA has not shown significant differences in prediction time due to cultural differences. Thus, no further statistical analysis is conducted. However, with regard to the focus of the research, the descriptive statistic is calculated to investigate the effect of differences in cultural background on prediction times. Figure 3.5 shows the error bar chart of the culture variable. It shows that the mean prediction time of the Asian participants (mean = 6019.887 ms, SD = 4002.841 ms) is higher than that of the European groups (mean = 5900.918 ms, SD = 3848.234 ms).

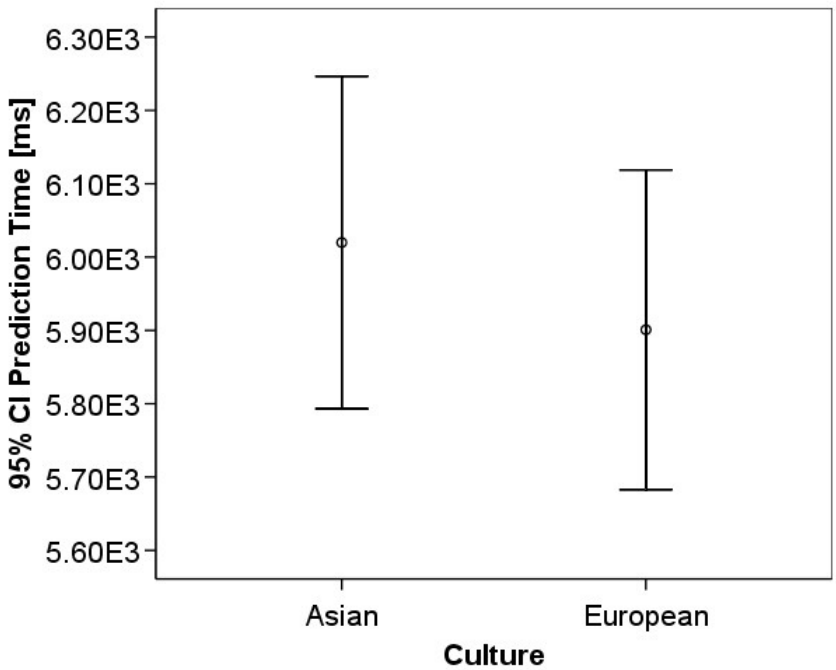


Figure 3.5. The error bar chart of the prediction times from the two different cultural groups (Study 1).

- Assembly Group

The ANOVA result for the assembly groups show that the *p*-values is less than 0.05 ($p \leq 0.001$). Therefore, a post hoc test based on Bonferroni correction is performed as shown in Table 3.5 and described in an error bar chart in Figure 3.6.

Table 3.5 The post hoc test result for the assembly group (Study 1).

	HO1	HO2	PY1	PY2	SH1	SH2
HO1		.017*	.020*	.000*	.000*	.116
HO2	.017*		1.000	1.000	1.000	1.000
PY1	.020*	1.000		1.000	1.000	1.000
PY2	.000*	1.000	1.000		1.000	.669
SH1	.000*	1.000	1.000	1.000		.955
SH2	.116	1.000	1.000	.669	.955	

* $p < 0.05$

The Bonferroni post hoc test regarding the assembly groups (Table 3.5) indicates significant differences between HO1's interim state and the other interim states, except between HO1 and SH2. Other pairwise comparisons do not lead to significant differences.

Figure 3.6 shows the prediction times for each interim state. PY2 and SH1 turn to be the shortest prediction time in contrast to HO1.

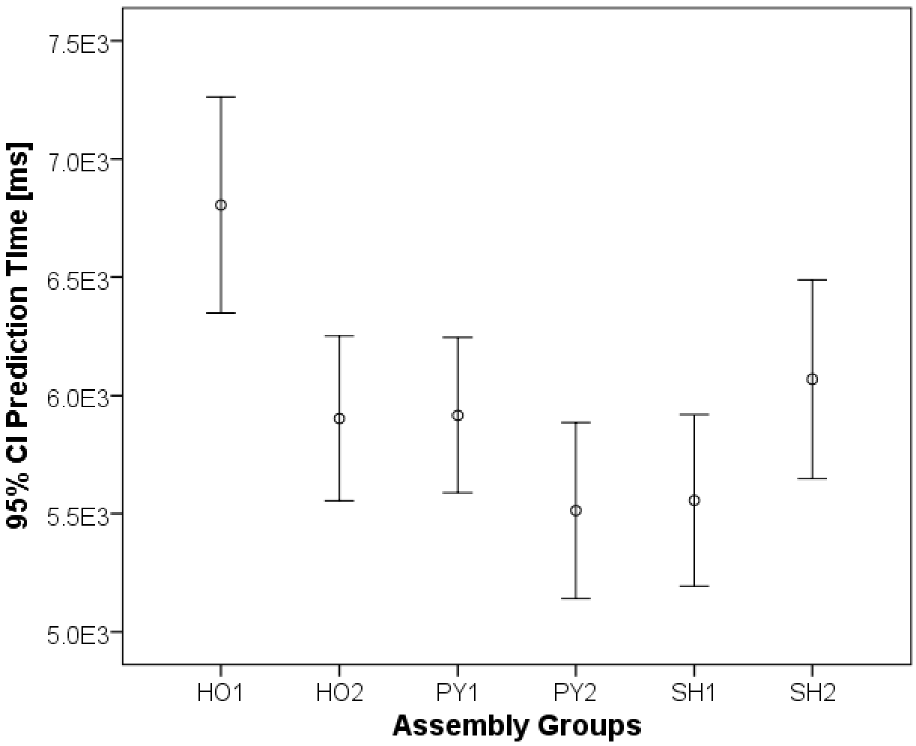


Figure 3.6. The error bar chart of prediction times required for the six different interim states (Study 1).

Subjective Evaluation

- Task load

The statistical analysis shows a normal distribution for the task load (*p = 1.000*) and the variance is homogeneous (*p = 0.437*). Thus, an ANOVA test is conducted statistically to investigate the task load.

According to ANOVA, there is a significant difference in the task load over time ($p \leq 0.001$). Figure 3.7 shows the mean chronologically and 95% CI of the task load.

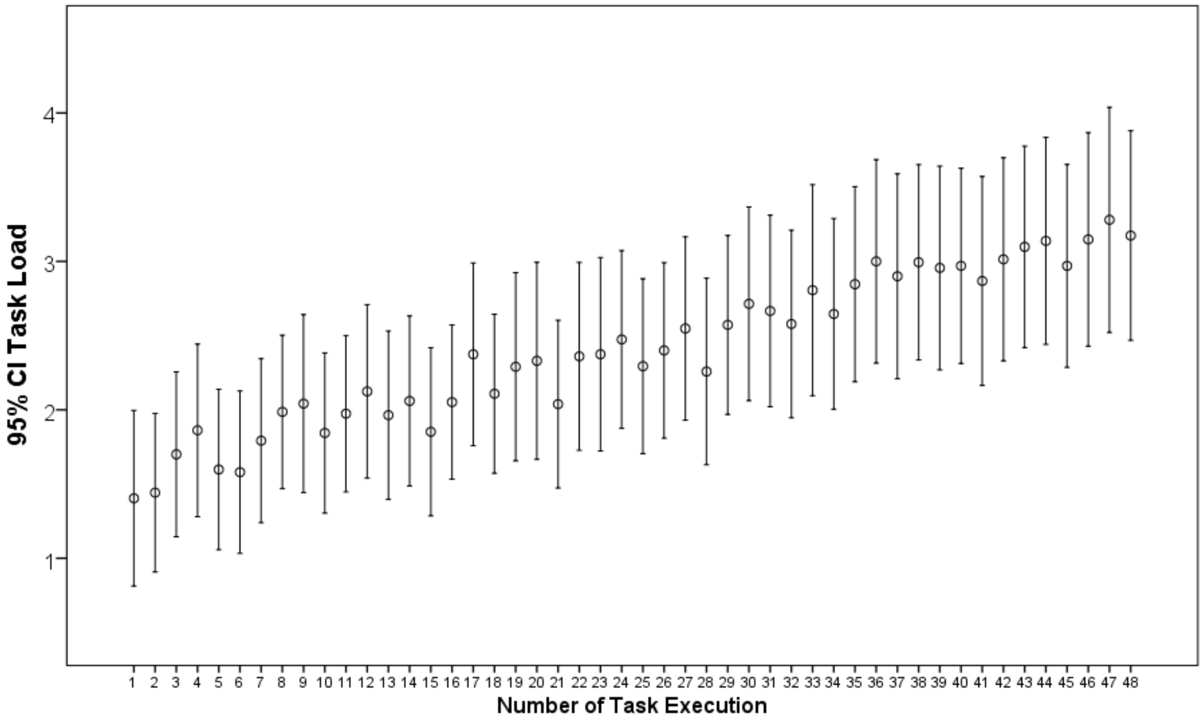


Figure 3.7. Chronological error bar chart of the task load in Study 1.

An ANOVA is conducted due to the necessity for differentiation analysis between the independent variables and their interactions. Table 3.6 shows the results of the ANOVA for the task load. The ANOVA is conducted to analyze the influence of the robot behavior model, the kinds of assembly groups, the assembly history information and the influence of culture on the task load of the participants. The ANOVA test result shows a significant difference of task load for the model of robot behavior variable ($p = 0.035$). Hence, H_5 is rejected, while H_6 ($p = 0.642$), H_7 ($p = 0.532$) and H_8 ($p = 0.285$) are not rejected.

Table 3.6 The ANOVA result for task load in Study 1.

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Culture	5.812	1	5.812	1.144	.285
Model	43.687	3	14.562	2.867	.035*
History	1.990	1	1.990	.392	.532
Assembly group	17.149	5	3.430	.675	.642
Culture * Model	4.575	3	1.525	.300	.825
Culture * History	.061	1	.061	.012	.913
Culture * Assembly group	5.362	5	1.072	.211	.958
Model * History	8.846	3	2.949	.580	.628
Model * Assembly group	43.120	15	2.875	.566	.902
History * Assembly group	8.512	5	1.702	.335	.892
Culture * Model * History	1.022	3	.341	.067	.977
Culture * Model * Assembly group	11.594	15	.773	.152	1.000
Culture * History * Assembly group	1.268	5	.254	.050	.998
Model * History * Assembly group	16.035	15	1.069	.210	.999
Culture * Model * History *Assembly group	21.067	15	1.404	.276	.997

*p<0.05

- Model of Robot Behavior

A post hoc comparison according to Bonferroni correction with a level of significance α = 0.05 is performed for the model of robot behavior. It shows a significant difference between Model 1 and Model 4 (*p = 0.022*). Model 1 leads to the highest task load. On the contrary, Model 4, as the most human-oriented model, leads to the lowest task load. Other variables and the interaction between variables have not statistically shown any significant differences. Table 3.7 describes the post hoc test for the task load, while Figure 3.8 describes the error bar chart of task load depending on the model of robot behavior.

Table 3.7 The post hoc test result for the task load based on the model of robot behavior (Study 1).

	Model 1	**Model 2**	**Model 3**	**Model 4**
Model 1		1.000	1.000	.022*
Model 2	1.000		1.000	.502
Model 3	1.999	1.000		.515
Model 4	.022*	.502	.515	

*p<0.05

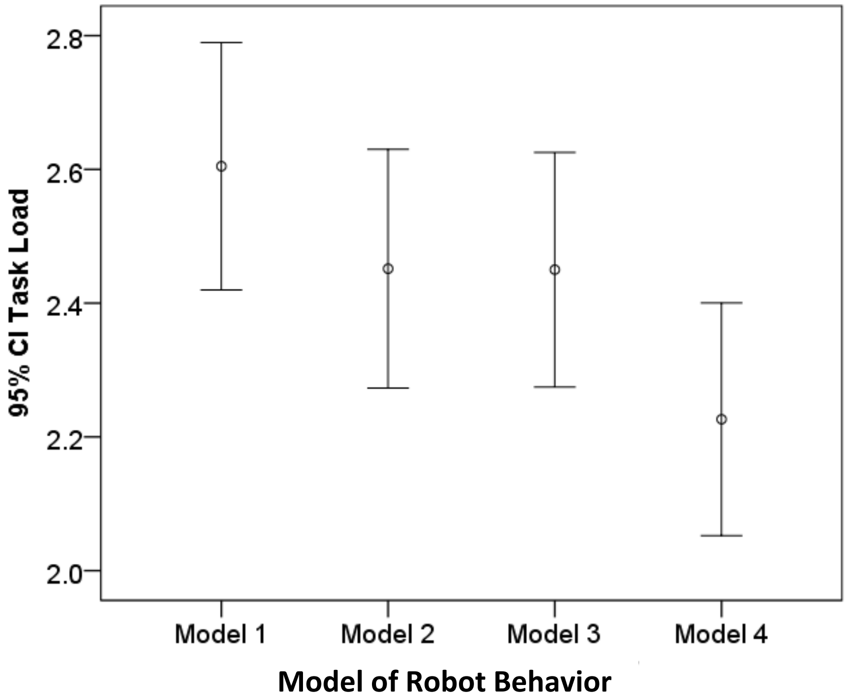


Figure 3.8 The error bar chart of the task load for the four different models of robot behavior (Study 1).

- Cultural Differences

The ANOVA shows that the culture does not lead to significant differences in the task load examination. Thus, further statistical analysis is not conducted. A descriptive statistic is calculated to show the differences in task load based on culture differences as shown in Figure 3.9. It shows that the task load of the Asian group (mean = 2.5, SD = 2.3) is higher than the European group (mean = 2.4, SD = 2.1).

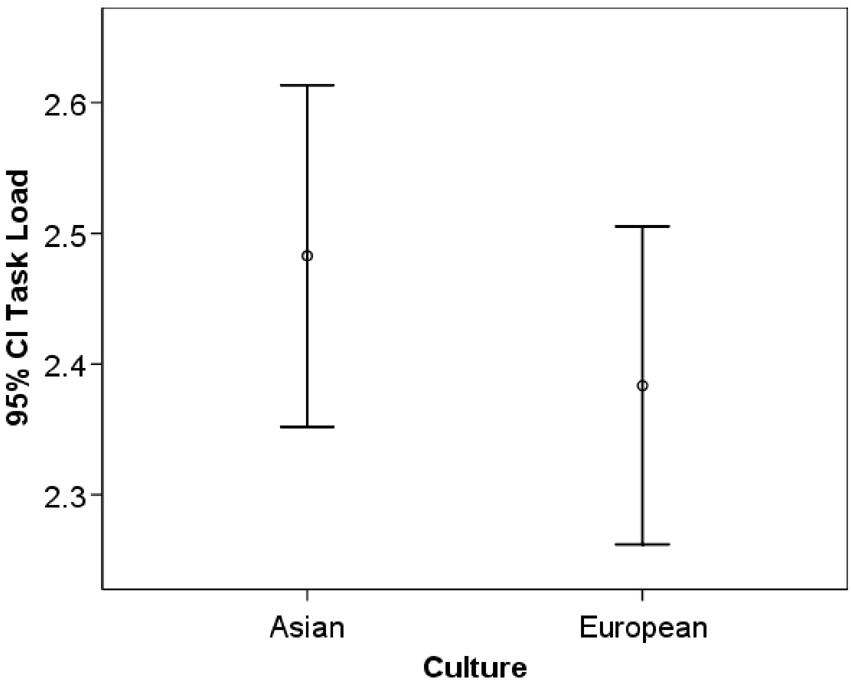


Figure 3.9 The error bar chart of the task load for the two different cultures (Study 1)

- Dissatisfaction Grade

Based on the normality distribution test, the dissatisfaction grade during study 1 indicates a normal distribution (*p = 1.000*). The Levene's test shows that the variance is homogeneous (*p = 0.901*). Hence, an ANOVA is conducted to statistically investigate the dissatisfaction grade of the participant concerning the assembly sequence performance. The analysis is run based on chronological analysis, dependent variables and independent variables.

ANOVA's test has not shown a significant difference in the degree of dissatisfaction chronologically (*p* = 0.479). Figure 3.10 depicts the error bar chart of the dissatisfaction grade chronologically.

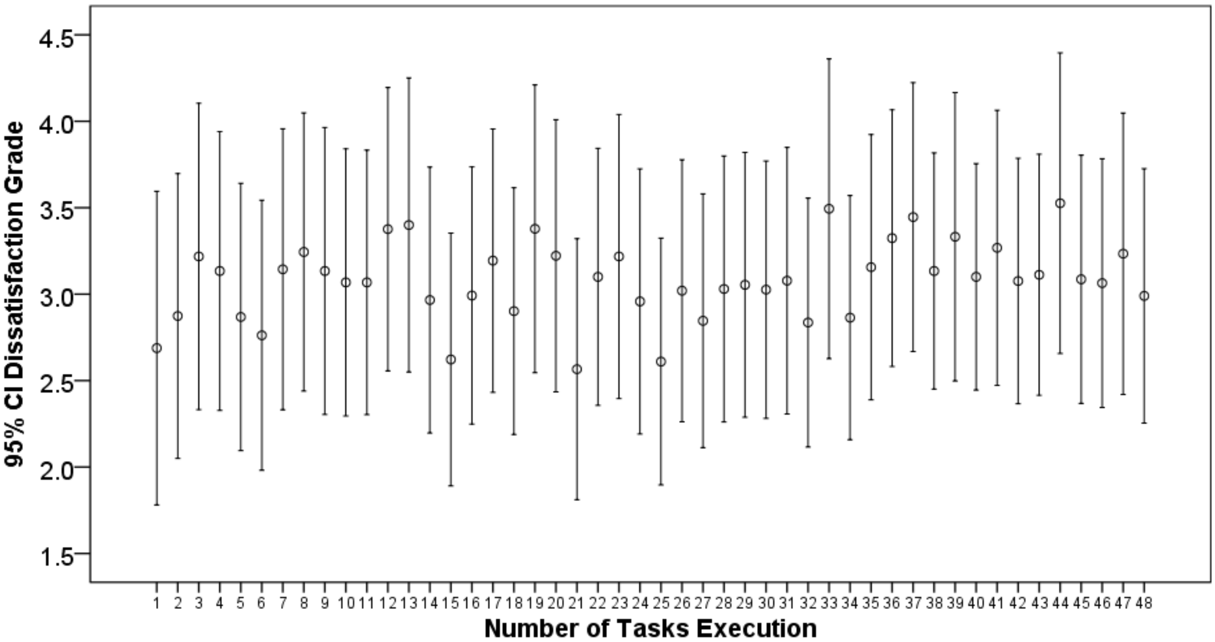


Figure 3.10 Chronological error bar chart of the dissatisfaction grade in Study 1.

An ANOVA is also carried out to examine the independent variables in the dissatisfaction grade during task completion. Table 3.8 describes the details of the ANOVA result on the dissatisfaction grade.

Table 3.8 The ANOVA results for the dissatisfaction grade (Study 1).

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Culture	10.640	1	10.640	1.452	.228
Model	296.639	3	98.880	13.494	.000*
History	9.856	1	9.856	1.345	.246
Assembly group	67.436	5	13.487	1.841	.102
Culture * Model	39.662	3	13.221	1.804	.144
Culture * History	.066	1	.066	.009	.924
Culture * Assembly group	9.460	5	1.892	.258	.936
Model * History	5.782	3	1.927	.263	.852
Model * Assembly group	69.211	15	4.614	.630	.853
History * Assembly group	12.002	5	2.400	.328	.897
Culture * Model * History	4.085	3	1.362	.186	.906
Culture * Model * Assembly group	49.538	15	3.303	.451	.964
Culture * History * Assembly group	6.263	5	1.253	.171	.973
Model * History * Assembly group	32.639	15	2.176	.297	.996
Culture * Model * History * Assembly group	31.408	15	2.094	.286	.997

*p<0.05

The ANOVA test result also indicates a significant difference in the model of robot behavior variable ($p \leq 0.001$). Therefore, H_9 is rejected, while H_{10} ($p = 0.102$), H_{11} ($p = 0.246$) and H_{12} ($p = 0.228$) are not rejected.

- Model of Robot Behavior

The pairwise comparisons using a Conferring correction between the models of robot behavior variable are taken into account. Table 3.9 provides the pairwise comparisons. Figure 3.11 illustrates the error bar chart of participant dissatisfaction depending on the model of robot behavior during Study 1.

Table 3.9 The Post Hoc test result of the dissatisfaction grade based on the model of robot behavior (Study 1).

	Model 1	**Model 2**	**Model 3**	**Model 4**
Model 1		1.000	.868	.000*
Model 2	1.000		1.000	.000*
Model 3	.868	1.000		.000*
Model 4	.000*	.000*	.000*	

* p<0.05

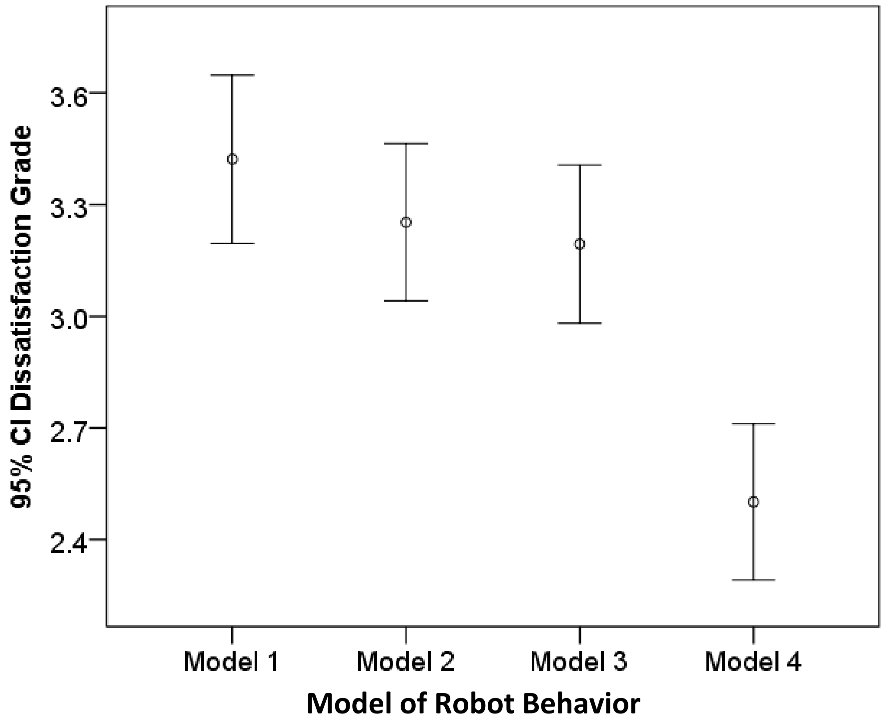


Figure 3.11 The error bar chart of the dissatisfaction grade for the four different models of robot behavior (Study 1).

In contrast to the results regarding the task load, the participant dissatisfaction grade leads to a significant difference between Model 4 and all other models (*$p \leq 0.001$*). Figure 3.11 shows the grade of participant dissatisfaction. Model 4, which incorporates the highest number of human-oriented production rules in its knowledge base, leads to a grade of less dissatisfaction from the participant concerning the clearness of the assembly sequence guidance.

- Cultural differences

The ANOVA has not shown significant differences in the culture variable. A descriptive statistic is then conducted to clarify the differences in dissatisfaction grade based on the culture variable. Figure 3.12 shows the error bar chart of the dissatisfaction grade depending on the different culture group. Figure 3.12 illustrates that the dissatisfaction grade of the Asian group (mean = 3.2, SD = 2.8) is higher, and shows lower levels dissatisfaction in the European group (mean = 3.0, SD = 2.6).

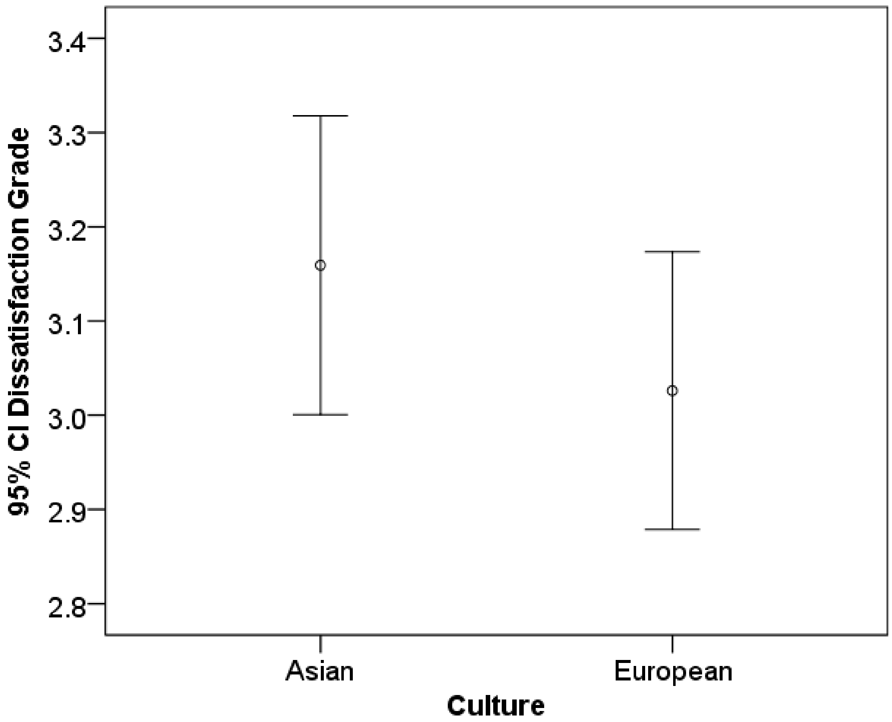


Figure 3.12 The error bar chart of the dissatisfaction grades of the two different cultures (Study 1).

- Assembly Strategy Evaluation

Since a non-parametric analysis is required to assess the participant's experience, the Cochran and McNemar tests (Field, 2005) are conducted based on model variants. The participants evaluate whether the simulated behavior of the robot is strategic or stochastic.

- Model of Robot Behavior

According to Cochran's Q test, there is a significant difference in the evaluation among the four models of assembly strategy ($\chi^2(3) = 3.13E+2$, $p < 0.05$). As a result, hypothesis H_{13} is rejected. In order to compare the pattern across the four models of robot behavior with the research hypothesis, all pairwise comparisons among all of the design conditions using McNemar test are needed (see Table 3.10).

Table 3.10 The pairwise comparisons between the models of robot behavior (Study 1).

	Model 1	Model 2	Model 3	Model 4
Model 1		.000*	.000*	.000*
Model 2	.000*		.892	.000*
Model 3	.000*	.892		.000*
Model 4	.000*	.000*	.000*	

* p < 0.05

The pairwise comparisons using the continuity-corrected McNemar's tests with Bonferroni correction reveal that there are significant differences ($p < 0.05$) in the assembly strategy evaluation between the models. The significant differences are on the whole indicated in pairwise comparison of models except the comparison between Model 2 and Model 3. The subjective evaluation of assembly strategy by participants is depicted in Figure 3.13.

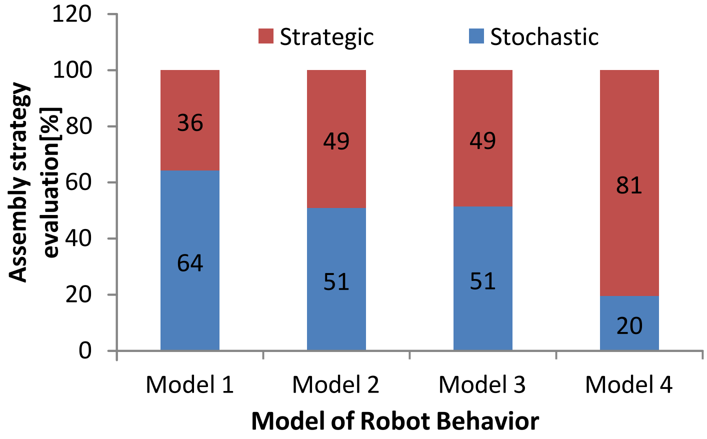


Figure 3.13 The assembly strategy evaluation for the four different models of robot behavior (Study 1).

- Cultural differences

The Cochran's test for culture shows a significant difference ($\chi^2(1) = 5.816$, $p = 0.016$). Thus, hypothesis H_{14} is rejected. The pairwise comparison also clarifies a significant difference between the Asian and the European groups *(p = 0.018).* The differences in assembly strategy evaluation based on the culture for the each model is shown in Figure 3.14. It shows that Model 4 is a strategic method both for the Asian and the European participants.

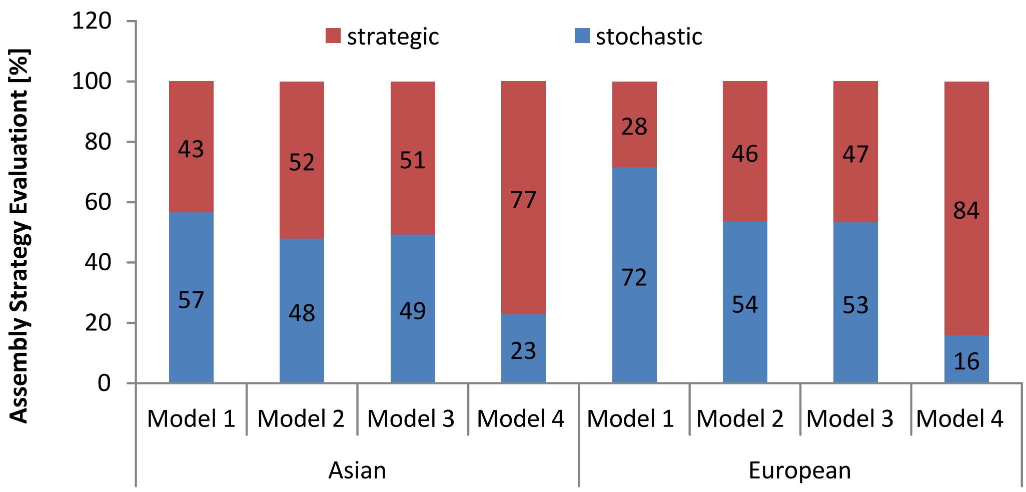


Figure 3.14 The assembly strategy evaluation for the two different cultures (Study 1).

Position of the Observed Brick

The results of the statistical analysis show significant differences in prediction times regarding the main variables of robot behavior model and assembly group. As a further discussion, the position of predicted brick is studied regarding differentiations between models of robot behavior and the assembly groups.

Based on the model of robot behavior, there are five possibilities in predicted brick positions. Each robot behavior model results in different position possibilities. For example, Model 4, which represents the most human-oriented model, expects only one position of predicted brick, while Model 1 – as the least human-oriented model – expects equal distribution for five position possibilities. Figure 3.15 shows the possibilities in predicted brick positions for each interim state.

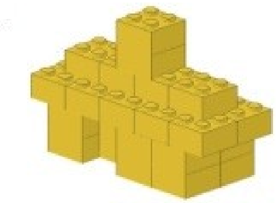
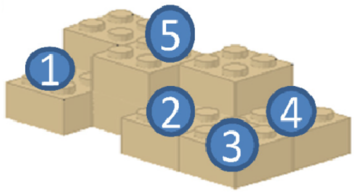
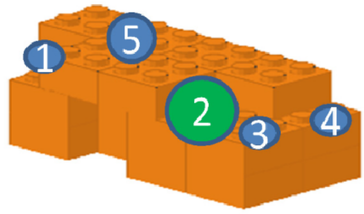
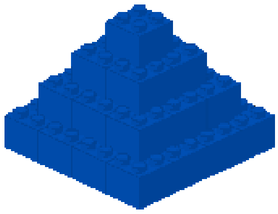
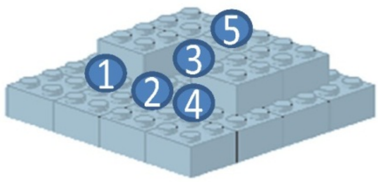
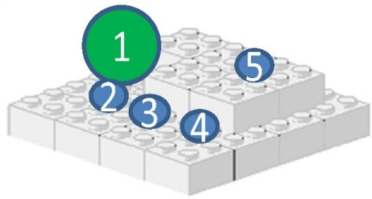
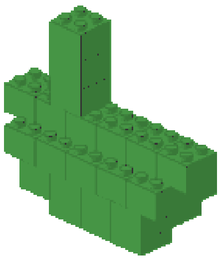
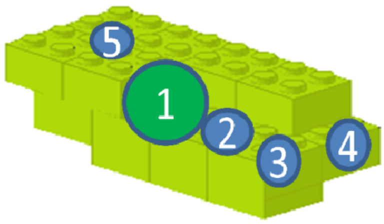
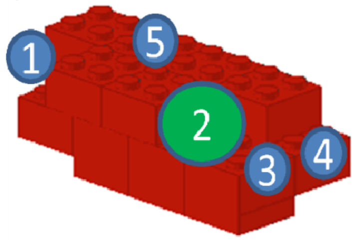
No	Assembly groups	Interim State	
1	House 	HO1 	HO2 
2	Pyramid 	PY1 	PY2 
3	Ship 	SH1 	SH2 

Figure 3.15 The possibilities in predicted brick positions (Study 1).

Study 1 reveals the difference distribution for each model of robot behavior. Figure 3.16 shows in detail how each model defines the different expectation and observation positions of the predicted brick, while Figure 3.17 describes the expectation and observation positions based on assembly groups.

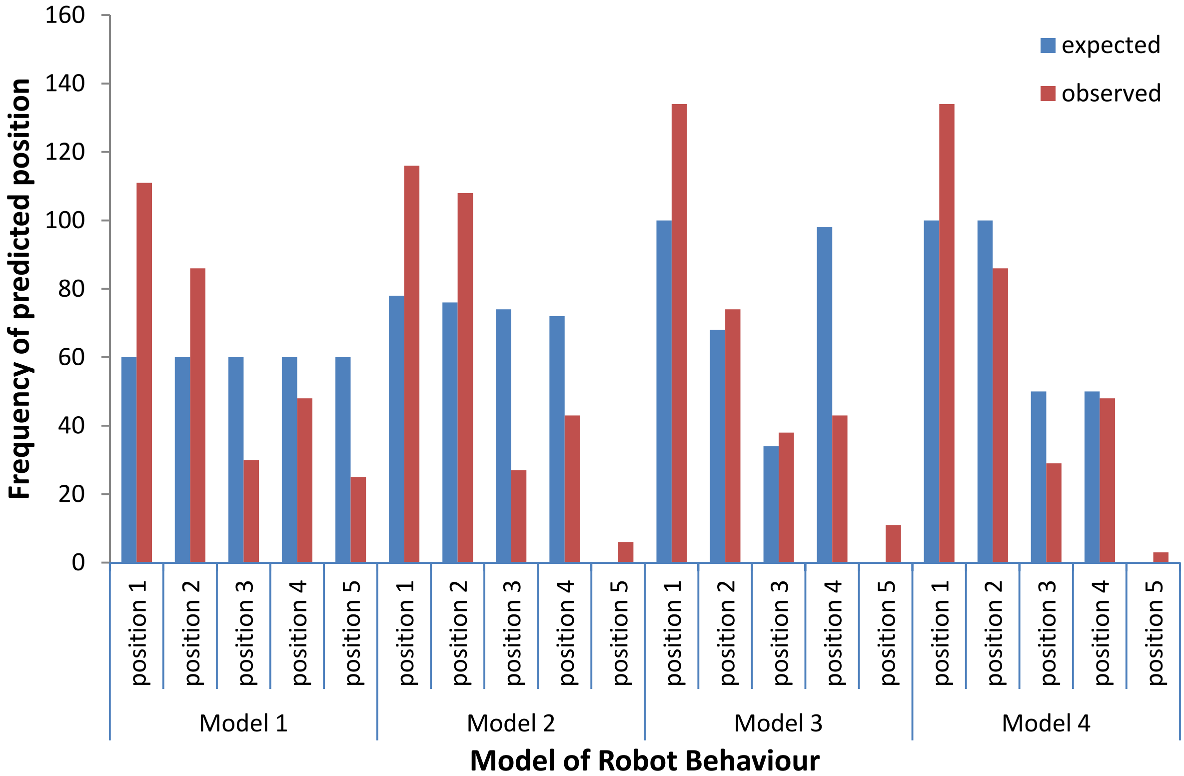


Figure 3.16 Distribution of the observed and the expected position of the brick based on the model of robot behavior (study 1).

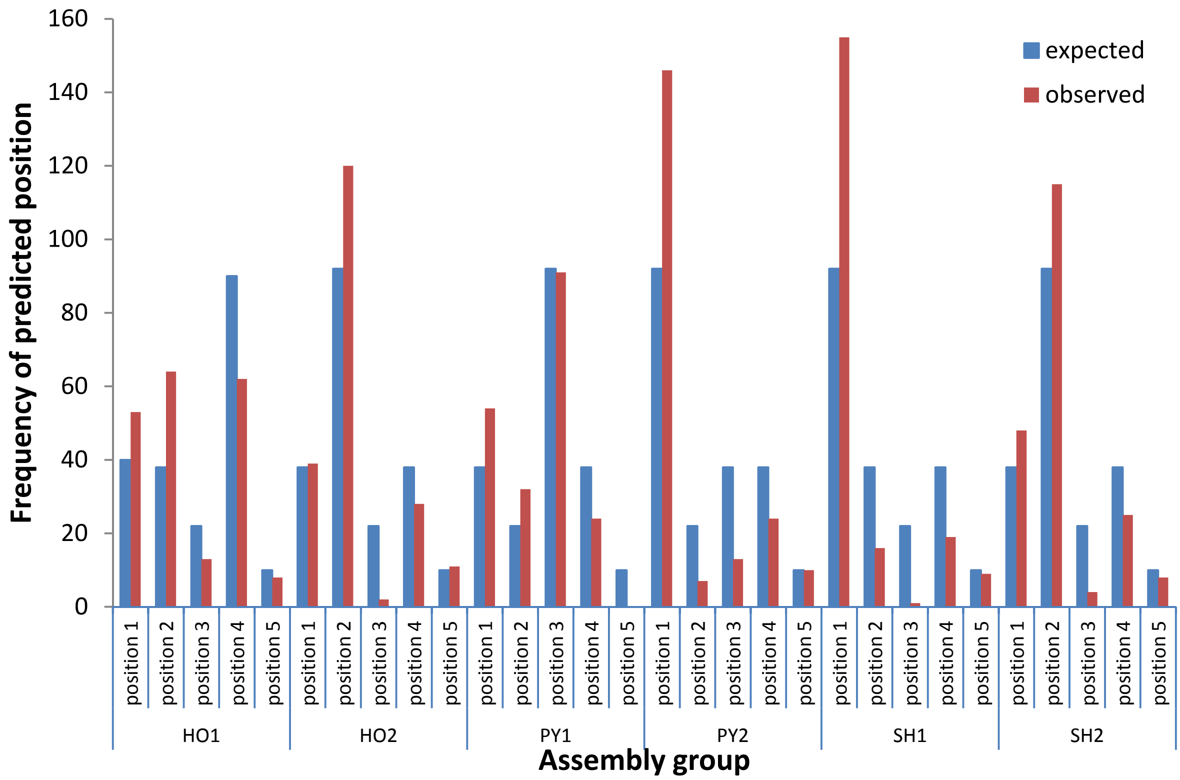


Figure 3.17 Distribution of the observed and the expected position of the brick based on the assembly group (study 1).

Table 3.11 summarizes the observed position of the predicted brick (referring to Figure 3.15) based on culture and assembly group. As presumed before, Asian and European participants have not shown significant differences.

Table 3.11 Summary of the observed position of the predicted brick (Study 1).

Assembly groups	ASIAN	EUROPEAN
HO1	Position 4, 1 and 2	Position 4, 1 and 2
HO2	Position 2 for all rules (44-80%)	Position 2 and 1
PY1	Position 3, 1 and 2	Position 3, 1 and 2
PY2	Position 1 for all rules (60-88%)	Position 1 for all rules (56-96%)
SH1	Position 1 for all rules (68-92%)	Position 1 for all rules (52-100%)
SH2	Position 2 for all rules (44-72%)	Position 2 for all rules (40-76%)

Furthermore, predictive accuracy is taken into account to examine the accuracy of the prediction of the robot behavior models in the prediction task. Predictive accuracy is defined as the relative frequency of the correct position of the predicted brick. The relative frequency is determined based on the deviation between the expected and observed brick position. It is defined as the ratio of the absolute difference between the expected and observed position $|\Delta|$ and the total deviation related to the main variable. The predictive accuracy (PA) related to model *i* can therefore be expressed by:

$$PA_i = 1 - \left(\frac{|\Delta model_i|}{total\ deviation}\right) \qquad (3.1)$$

In this study, deviation is defined as the difference between the numbers of observed and expected brick positions. The data of the position deviation is shown in Table 3.12, which also depicts the deviations regarding the main variables.

Table 3.12 Deviation of the predicted brick position (Study 1).

		HO1		**HO2**		**PY1**		**PY2**		**SH1**		**SH2**	
		5	**7**	**5**	**7**	**5**	**7**	**5**	**7**	**5**	**7**	**5**	**7**
Asian	Model 1	14	16	18	20	15	16	26	20	24	24	18	24
	Model 2	14	14	20	22	14	13	26	24	22	26	18	14
	Model 3	10	8	16	8	12	22	18	18	28	22	12	8
	Model 4	13	15	8	5	14	16	3	4	2	5	11	7
European	Model 1	16	12	26	22	18	22	22	24	24	26	24	22
	Model 2	10	10	17	22	12	14	16	28	20	18	18	14
	Model 3	14	14	14	14	18	10	24	24	22	22	10	8
	Model 4	9	12	11	7	14	11	1	1	1	0	7	6

The statistical analysis of deviation levels is conducted by using the chi-square test for each main variable. The result of the chi-square test is showed in Table 3.13.

Table 3.13 The chi-square test results for deviations in predicted brick position (Study 1).

	χ^2	df	p
Model	139,482	3	0,000*
Assembly group	19,208	5	0,002*
History	0,068	1	0,795
Culture	0,173	1	0,677

*p<0.05

Based on the chi-square test, the models of robot behavior and the assembly groups show significant differences. Thus, the differences in predictive accuracy between the models of robot behavior should be taken into account.

The predictive accuracy depending on the model of robot behavior and the assembly group is graphically described in Figures 3.18 and 3.19.

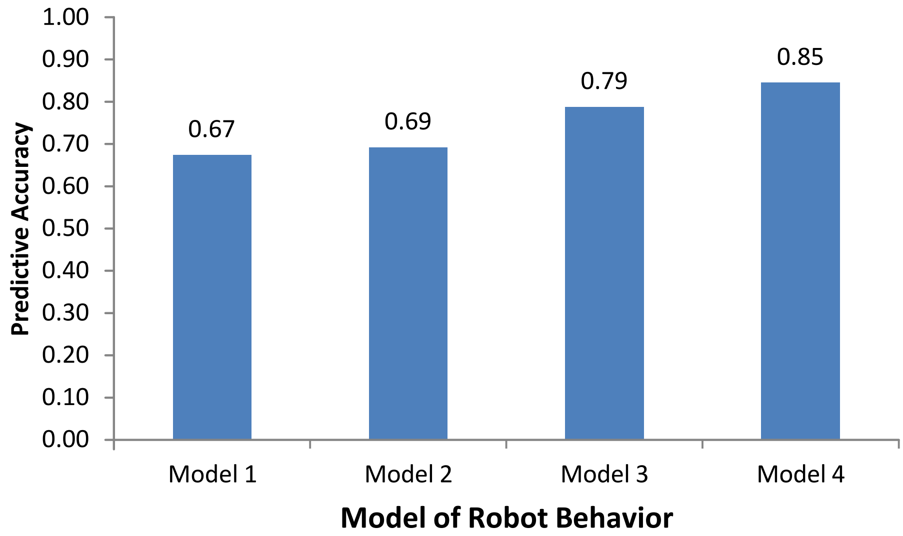


Figure 3.18 The predictive accuracy for the four different models of robot behavior (Study 1).

According to Figure 3.18, Model 4, as the human cognition representation, leads to the highest predictive accuracy, i.e. 85% of the expected brick positions are predicted correctly and only 15% incorrectly. On the other hand, Model 1 as the reference model without any human-oriented production rules leads to the lowest predictive accuracy. These findings indicate that the human behavioral pattern leads to a better predictability of assembly strategy due to the conformity between the expected and the observed results.

The assembly group variable leads to differences in the predictive accuracy as shown in Figure 3.19. The highest predictive accuracy is observed in the SH1 interim state (PA = 0.91), while the lowest predictive accuracy is observed in the HO2 interim state (PA = 0.75).

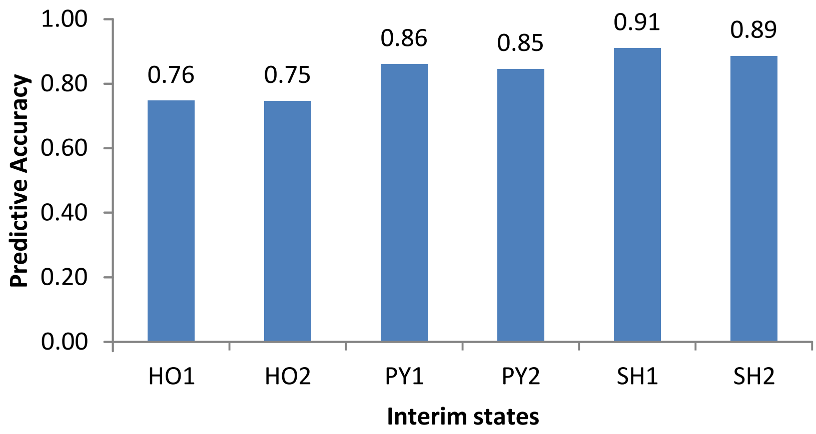


Figure 3.19 Predictive accuracy for the six different kind of assembly group (Study 1).

The culture variable has not shown significant deviation. However, with regard to the focus of research, Figure 3.20 describes the predictive accuracy based on the culture variable for each model. For instance, the predictive accuracies with Model 4 show the highest predictive accuracy for both the Asian (PA = 0.87) and the European (PA = 0.89) groups.

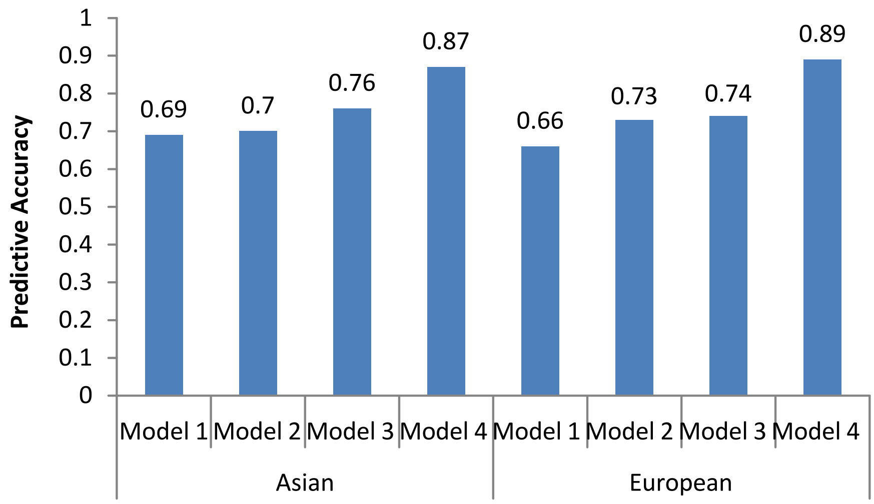


Figure 3.20 The predictive accuracy of the two different culture groups (Study 1).

Based on the data of Study 1, it can be concluded that the model of robot behavior is the most influential variable for prediction time and predictive accuracy. The model is capable of adapting itself to both the assembly conditions and the combination of other variables in the work system. The assembly groups affect the work process based on the different interim states. The assembly groups also influence the work system based on the interim states. The prediction position is consistent for the interim states that have a similar design. Each model and assembly group used in the assembly task leads to a different brick position (see Table 3.12). Assembly sequences in the assembly task with lengths of 5 and 7 have a similar effect on the predicted position. The Asian and European participants have similar tendencies regarding the predicted position in the equal design of interim states (such as HO2 - SH2 and PY2 - SH1) as explained in Table 3.11.

3.1.3 Discussion

To evaluate the compatibility of human cognition with the technical system, different cognitive simulation models to control robot behavior in assembly tasks were developed and evaluated (Mayer et al., 2011). A basic product made from the LEGO bricks is used for Study 1. The results of Study 1 statistically prove that the human-oriented production rules incorporated in the knowledge base of Model 4 lead to a higher performance of the participants. The results are confirmed based on the prediction time and subjective evaluations.

Prediction Time

The prediction time is the primary dependent variable in this study. It represents the duration between the end of assembly sequence visualization on the screen until the participants finish their positioning task. The prediction time data is analyzed using an ANOVA. The analysis is conducted for the correct prediction result depending on the model of robot behavior. The results show significant differences between the models of robot behavior and the assembly groups.

According to the pairwise comparison analysis of the model of robot behavior, Model 2 and 3 have not shown significant differences concerning the prediction times. This result indicates that the participants as human operators do not comprehend the distinction between these strategies. On the other hand, comparisons of Model 4 against the other models show significant differences. These results indicate that Model 4 stimulates comprehension of the assembly strategy and accelerates the learning process of the following action prediction.

Model 4, as the most human-oriented model, results in the shortest prediction time (mean = 5334.215 ms, SD = 3761.30 ms), while Model 2 leads to the longest prediction time (mean = 6357.122 ms, SD = 4329.879 ms). Model 2 using neighborhood and layer strategies in a weak relationship cause confusion due to the neighborhood between layers. The sequences based on these strategies do not follow the patterns of human assembly behavior. The reference Model 1 is established without any production rules in assembly sequences. As a result, the participants require more time to learn and analyze this assembly strategy, especially when they have to determine a position for the next brick. A human has a tendency to predict the position of the next brick based on his or her prior experience as explained by Hou and Wang (2010). The assembly task operation includes workpiece activity and non-workpiece activity. In each assembly step, the human worker conducts a physical workpiece activity (e.g., observing, grasping, installing) and a mental non-workpiece activity (e.g., comprehending, translating and retrieving information). Once the current step finishes, the human worker will recommence this physical and mental behavior in the next assembly step. This means it is an expected behavior of human cognition to apply previous knowledge and experience to the next task. If the next step is incompatible with the prior knowledge, the human will take a longer time to adapt to and learn the current step. Furthermore, the learning process during the assembly process becomes longer due to the discrepancy between the prediction and the observed robot motion.

The cultural background results have not shown significant differences. A descriptive statistical analysis is conducted to describe the differences in prediction times based on culture. Figure 3.5 shows that the European group required a shorter prediction time than the Asian group. This result is in line with the study of Mann (1998) that the Westerners are more confident in case of the decision making than the Asian group.

Based on the descriptive statistical calculation depending on the assembly group, the prediction time of PY2 (mean = 5513.612 ms, SD = 3793.64 ms) and SH1 (mean = 5556.255 ms, SD = 3692.504 ms) indicate the shortest prediction time, while HO1 leads to the longest prediction time (mean = 6804.690 ms, SD = 4653.979 ms). These facts indicate that a human tends to learn easily in a strategic pattern based on the peculiarity of the interim states toward the completed object state. In the interim state example, HO1 is not as easily conceived of as being a part of the house object than the other designs because it only has the first two of six layers. The bottom side of house design is covered by the top side so that the participants cannot see the completed construction inside the house. The neighborhoods rule is explicitly patterned in this interim state. PY2 and SH1 have a similar design to the remaining one place as shown in Figure 3.3 and explained in Figure 3.22. With this similarity, the participants experience and learn the strategy more often in this design than in the other interim state designs. Furthermore, the interim state design of PY2 and SH1 can obviously be identified as part of the pyramid and ship. Additionally, PY2 and SH1 also have the least complicated and well-structured design.

The post hoc test results for the assembly group indicate significant differences of the prediction times with the HO1 interim state compared to other interim states. On the other hand, the pairwise comparisons between HO2 towards PY1 and SH2 do not show significant differences in the sense of the prediction time of PY2 towards SH1.

The design of HO2 and SH2 form a T-shape with different arrangements of the assembly sequence (see Figure 3.21). It aims at determining the performance of the operator in assessing the assembly strategy and predicting the location of the next brick based on the similarity of the interim state design. The position of the next brick is 100% on position 2 (see Section 3.1). There are insignificant differences in prediction times and brick positions in those assembly groups. This fact demonstrates the consistency of the participants as human operators in the learning process and the prediction task. The assembly group affects the human operators when they make decisions and perform their work.

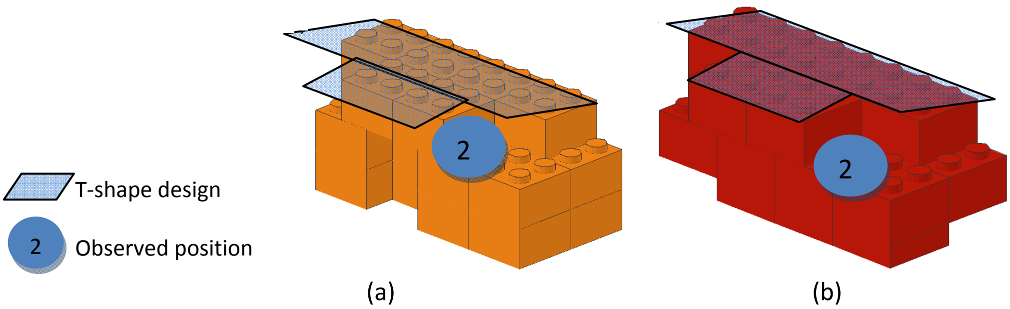


Figure 3.21 The similarity design of HO2 (a) and SH2 (b) interim states.

The other interim states lead to different distributions of brick positioning due to the variations in interim state designs. For example, HO1, PY2 and SH1 are designed with one position remaining at the end of the horizontal row. It is expected that the participants will position the next brick in either hole (see Figure 3.22). However, based on the sequences of SH1 assembly, the participants are expected to position the brick on position 1. The result of Study 1 shows that the participants tend to pay attention to the model of robot behavior rather than the design of interim state. The difference between the expected and observed positions of the next brick is found in HO1 interim state. The results of Study 1 indicate an almost equitable distribution of the five brick position possibilities as shown in Figure 3.23.

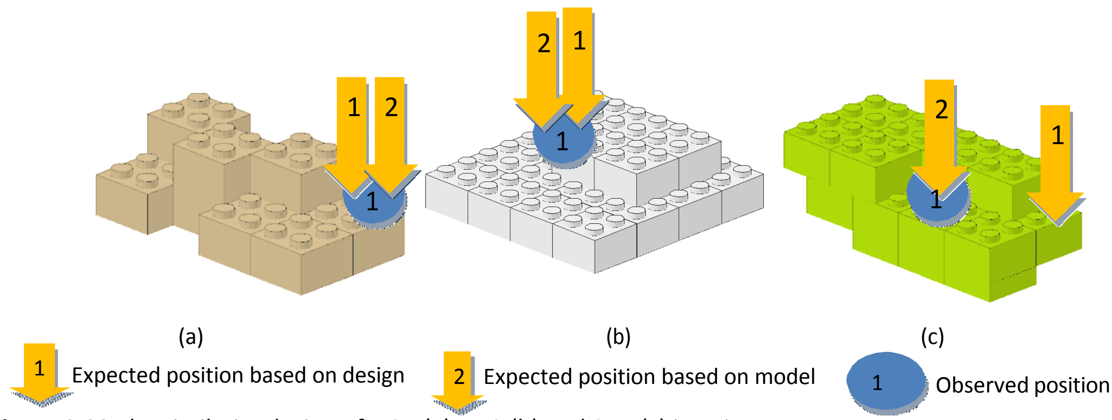


Figure 3.22 The similarity design of HO1 (a), PY2 (b) and SH1 (c) interim states.

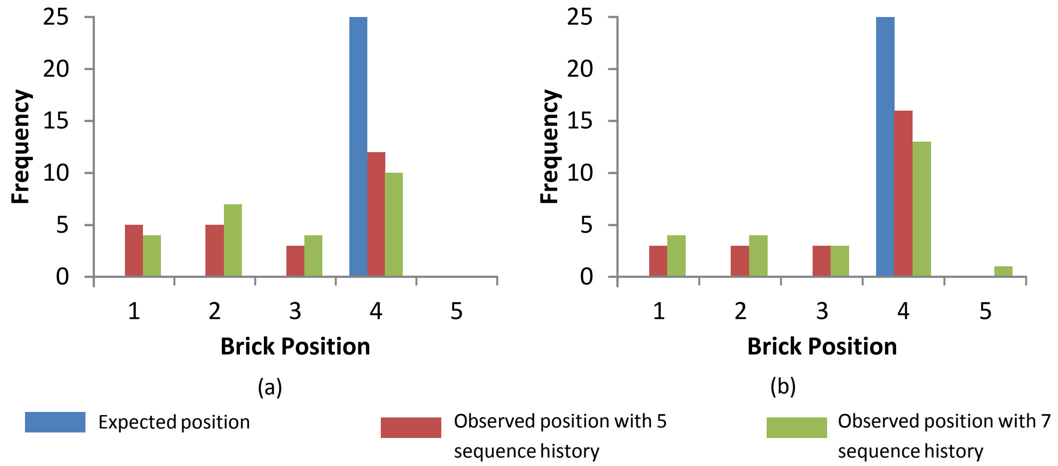


Figure 3.23 Brick position mapping of HO1 interim state on the Asian participants (a) and the European participants (b).

With slight differences to Mayer's (2012) research result, Study 1 only shows significant differences related the model of robot behavior and the assembly group as independent variables. Mayer (2012) states that the statistical analysis revealed significant differences regarding these main variables as well as their interaction. Thus, only the interaction between the model and the assembly group is further investigated.

Subjective Evaluation

- Task load

The participant's task load is ranged between 0 (very low task load) and 10 (very high task load). The task load increases along with the increasing number of tasks. For example, the mean grade of the participant's task load in the first task is 1.4. By Task 12 – as the last task in the first session – the mean grade of the participant's task load is 2.1. The grade by task 13 – as the first task on the second session – is slightly decreased (mean task load = 1.9), and it increases until task 24 – as the last task of the second session – (mean task load = 2.5). This condition is repeated until the last session in which the mean grade of the participant's task load in task 48 – as the last task of the fourth session – is 3.2. Moreover, the ANOVA also denotes significant differences in the task load data that are arranged chronologically.

According to the independent variables, the ANOVA only shows a significant difference in the task load for the models of robot behavior. There are no indications of significant differences in task loads for other main variables and the interaction between those variables. Furthermore, the post hoc analysis of the models shows significant differences in task load between Model 1 and Model 4. Model 1 – as the least human-oriented model – leads to the highest task load (mean = 2.6, SD = 2.3) due to the irregularity of the assembly sequence, while Model 4 – as the most human-oriented model – leads to the lowest task load (mean = 2.2, SD = 2.2). It evidently proves that a higher component of human behavior leads to a lower task load for the participants when predicting the position of the bricks .

As expected, cultural background does not lead to a significant difference in the task load evaluation. This result is in line with the study result of Chee et al. (2011). The result explains that the there are no significant difference between East Asian subjects and Westerner in hippocampal size when processing the visual information.

The results of this study are comparable to the findings of Mayer (2012) who describes a significant difference in the chronologically structured data of task load regarding the model of robot behavior as the main variable.

- Dissatisfaction Grade

The dissatisfaction grade describes whether the information about the assembly sequence visualized on the screen is well-understood by the participants. If the participants experience no difficulties in identifying the assembly sequence strategy, the dissatisfaction grade should be low. Grade 0 represents the lowest participant's dissatisfaction value due to the easiness and clarity of the assembly sequence instruction. Accordingly, grade 10 represents the highest dissatisfaction in the comprehensibility of the assembly sequence regarding greater difficulties in strategy identification.

The ANOVA of the dissatisfaction grades has not shown significant differences between task 1 and the further tasks in the chronological data arrangement. It implies that there is no influence of the increasing number of task on the participant's dissatisfaction grade.

On the other hand, significant differences are evident between the models of robot behavior in their ANOVA dissatisfaction grades. Similar to the task load, the pairwise comparisons between models show a significant difference between the dissatisfaction grade for Model 1 and Model 4. Model 1, which adopts only the MTM-1 rules, leads to the worst level of dissatisfaction (mean = 3.4, SD = 2.8), while the high degree of human assembly behavior in Model 4 leads to a better level of dissatisfaction grade (mean = 2.5, SD = 2.6). These facts highlight the clarity and prospective state of human assembly behavior as an assembly strategy.

The result of this variable is marginally different from Mayer (2012). There is a significant difference in the dissatisfaction grade due to the chronologically structured data (Mayer, 2012). The ANOVA test leads to a similar conclusion regarding the indication of significantly different dissatisfaction grades concerning the models of robot behavior.

The cultural backgrounds of participants do not have a significant effect on dissatisfaction. The error bar chart in Figure 3.12 shows that the dissatisfaction grade of the Asian group is higher than the European group. This means that the Asian group experiences more difficulty in the strategy comprehension than the European group.

- Assembly Strategy Evaluation

The last subjective evaluation of participants during the prediction task is assembly strategy evaluation. The participants are expected to decide whether the assembly sequence visualized on the screen follows a strategic or stochastic sequence.

With respect to the McNemar's test results, significant differences in assembly strategy evaluation are due to the models of robot behavior. On the whole, significant differences are indicated in pairwise comparisons of the models, with the exception of the comparison between Model 2 and Model 3. It is evident that a strong or weak relationship between the neighborhood and the layer design rules is not interpreted by the participants as a different strategy. The most human-oriented model in Model 4 is perceived by the participants as an easily captured and applied strategy in the assembly sequences (81%), while Model 1 – as the least human-oriented model in terms of the least number of production rules – is an incomprehensible and an elusive strategy that is largely perceived as a stochastic strategy (64%).

Similar results of this study and Mayer's study (2012) regarding assembly strategy evaluation are revealed in the McNemar test. Here, there are significant differences between the models of robot behavior. The assembly sequences based on simulated human cognition are recognized by the participants as a strategic approach.

The assembly strategy evaluation based on cultural background indicates a significant difference between the Asian and European groups. Model 4, as the most human-oriented model, is recognized as having a strategic mode of assembly strategy by both from the Asian (77%) and the European (84%) participants.

Predictive Accuracy

Predictive accuracy is considered by means of calculating the deviation between the observed and the expected brick position. Model 4 – as the representation of the most human-oriented model in the robotic assembly process – yields the highest predictive accuracy. Based on the categorization of culture, both the Asian and the European groups achieve the highest predictive accuracy when they work with Model 4. The predictive accuracy of the Asian group is lower than that of the European group. However, the difference is insignificant.

3.2 Study 2

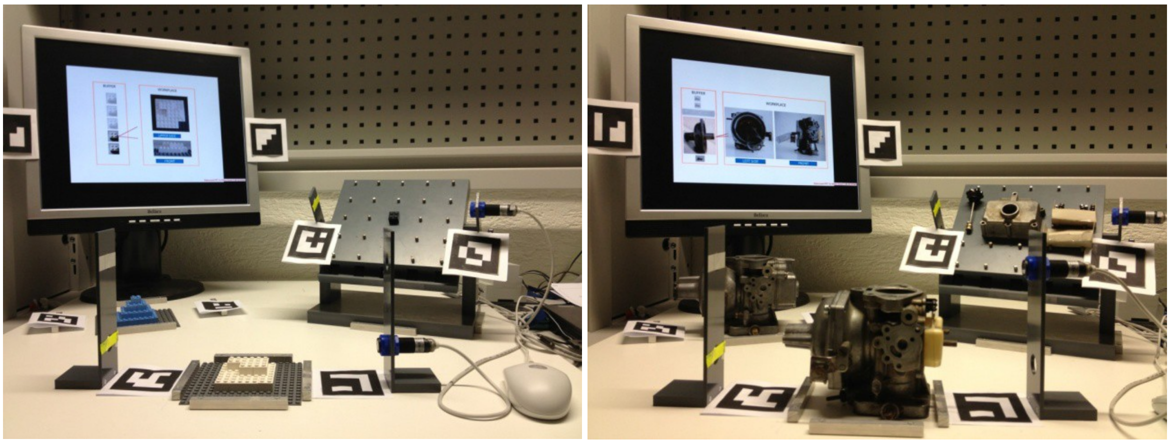
3.2.1 Objective and Method

Study 2 aims at transferring the strategies of human cognition to a real manufactured product, as well as data replication. Study 1 only used a simplified product made from LEGO bricks as a model of an assembly product that can be manufactured with a large number of variants. Therefore, Study 2 is conducted to examine whether the investigated human assembly strategies to ensure conformity in the expectation of the operator can be used to improve human performance related to an actual manufactured product.

The independent variables in Study 2 are elaborated by considering different age groups of participants and different kinds of assembly products. The length of prior assembly sequences is not taken into account due to the insignificant influence of this variable based on the results of Study 1. However, the cultural background of the participant is taken into account to evaluate whether the introduced approach to cognitive engineering is effective for different world regions.

Apparatus

The apparatus used in Study 2 is similar to that used in Study 1. Study 2 uses a 28” TFT screen to visualize the assembly sequence. There is an area for assembly work in front of the participant and an area for putting the completed product, as well as a table for the part that is used for the prediction task. A light barrier is operated to measure prediction time. The slightly different experimental environment is visualized from the central position that was used for the eye-tracking system. Figure 3.24 shows the main component used in Study 2.



(a) (b)

Figure 3.24 Environment of Study 2 (a) for the product made from LEGO bricks (b) for the carburetor.

An additional eye-tracking system is utilized in Study 2 due to the necessity to acquire gaze behavior and Area of Interest (AOI) data. The data is obtained using a head unit eye-tracking system that records the participants’ eye pupil movement when conducting and completing the study task. The head unit consists of an EyeCam to capture a high quality black and white video of the eye during the course of an experiment as well as a FieldCam to capture a high quality color of the field of vision of the subject. The video data recorded by the cams in the head unit are transmitted to the electronic unit in real time. The video data captures the area of interest of the subject during the study. This is shown by the recorded eye pupil movement of the working area and a heat map analysis. Figure 3.25 shows a different view on the experimental environment, in which the participant wears an eye-tracking system.

Figure 3.25 Environment of Study 2 with the eye-tracking system.

Independent Variables

Study 2 distinguishes four independent variables. These independent variables are the different models of robot behavior, kinds of the assembly groups, the cultural backgrounds of the participants, and the age of participants.

(1) Model of robot behavior (model)

Three models of robot behavior are used in Study 2. These models are adopted from study 1 with the same naming to simplify the analysis. Model 1, as the reference model, contains only MTM-1 rules (no human-oriented production rules are used at all). Model 3 represents a linear combination of the neighboring vicinity part and builds-up in layer strategies that have a strong relationship (neighborhood between layers is not allowed). Model 4 represents the most human-oriented model in terms of the highest number of human-oriented production rules. Model 2 is not included in Study 2 because of the insignificant difference between it and Model 3 based on the results of Study 1. Additionally, Model 3 is closer to the human strategy than Model 2. Hence, Model 3 is selected to examine the consistency and accuracy of participant predictions.

(2) Kinds of assembly group

Study 2 is based on two assembly products, and there are two interim states involved in each assembly group. Interim states are built to represent human assembly behavior and to evaluate the participant predictions (see Figure 3.26). Two products are evaluated, namely (1) products made from LEGO bricks as before and (2) a carburetor.

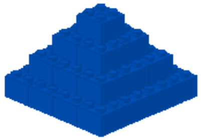
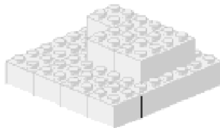
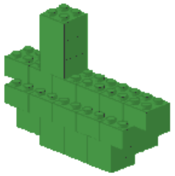
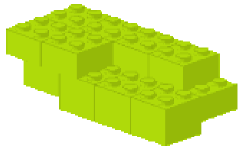
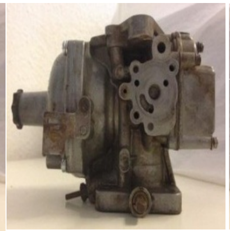
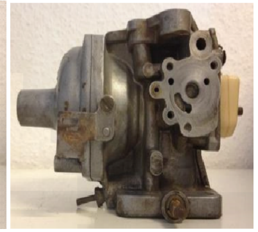
No	Product	Completed assembly groups	Interim State
1	LEGO	Pyramid (PY) 	
		Ship (SH) 	
2	Carburetor	   left side front side right side	Interim state carburetor 1    left side front side right side Interim state carburetor 2    left side front side right side

Figure 3.26 The Interim state and the completed assembly groups in Study 2.

(3) Cultural background

Similar to Study 1, participants are divided into two groups according to their cultural background. The cultural background is specifically selected for representing German and Indonesian cultures.

(4) Age

Study 2 categorizes participants into two age groups. The first group is younger (20-40 years old), while the second group represents older participants (41-60 years old).

To sum up, Table 3.14 shows the independent variables in Study 2.

Table 3.14 Independent variables of Study 2.

No	Study	Variable	Sub Variable
1	Prediction time and eye -tracking system	Models of robot behavior	Model 1 Model 3 Model 4
2	Prediction time and eye -tracking system	Kinds of assembly group	• Product made from LEGO bricks (pyramid and ship) • Carburetor
3	Prediction time and eye -tracking system	Cultural backgrounds	• German • Indonesian
4	Prediction time	Age groups of participants	• Younger (20-40 years old) • Older (41-60 years old)

The additional study using the eye-tracking system is conducted with 26 participants, which coincides with the prediction study. The prediction and AOI data are obtained simultaneously based on these combination systems. The eye-tracking system considers four independent variables. They are similar to the variables used in the prediction time study, except that there is an addition variable (area of interest), while the age variable is eliminated.

Study 2 considers four AOI in its environment. AOI 1 concerns the screen for assembly guidance visualization. AOI 2 covers the predicted LEGO brick or carburetor part. AOI 3 encompasses the assembly work area, while AOI 4 is designed to track eye activity in the completed assembly group area. Figure 3.27 presents the AOI in Study 2.

Figure 3.27 The areas of interest in Study 2.

Dependent Variable

The dependent variables of this study are the prediction times for performing a correct prediction, the subjective evaluation of the task load, the evaluation of a dissatisfaction grade, the evaluation of the assembly construction methods, and the fixation duration for each AOI of the participants during the assembly task.

Procedure

The procedure of Study 2 is similar to Study 1, except for using the eye tracking system on the participants. The procedure is divided into three main phases:

(1) Personal data collection and training under study conditions

First is the anonymized collection of personal data (e.g., age, education level, prior experience with the assembly task and LEGO assembly). The participant is introduced to the apparatus, the study environment the interim state and the completed object assembly group after the personal data are collected.

(2) Calibration of the eye-tracking system

Secondly, the calibration of the eye-tracking system is performed through the following procedures:

- Placing the head unit of the eye-tracking system on the participant's head.
- Starting the Dikablis recorder program and initiating eye detection.
- Calibrating the optical tracers based on standard areas.

(3) Data acquisition

The next phase consists of illustration and explanation of the assembly task to the participant. These explanations are visible on the monitor. After this, the participant is expected to notice the assembly pattern regarding the sequence of the LEGO brick or carburetor part placement. Furthermore, the participant has to determine the position of the next brick or the carburetor part with the real object after the visualization of the assembly of an interim state is finished. The prediction time is recorded and analyzed based on the independent variables. The evaluation of the assembly task (adapted from NASA-TLX) is conducted to examine the influence of human behavior on the assembly processes. The evaluations include the determination of the subjective task load (0 = low – 10 = high), dissatisfaction grade (0 = low – 10 = high) and strategy recognition. The area of interest and gaze behavior data is obtained from the eye-tracking system.

In total, there are 12 prediction tasks divided into two sessions (6 tasks for each session) with a randomized order of interim state and model. The duration per study is approximately 60 minutes for each person including personal data collection, eye-tracking system calibration and performing the required tasks.

Participants

A total number of 60 participants take part in the second study. From these, 30 participants represent each cultural background in two groups, which are further divided into two age groups (15 participants for each age group). The range of the average assembly experience grade of the participants is from 2.2 to 3.2. The experience levels range from 1 (low) to 5 (high). Table 3.15 describes the participant specifications in Study 2.

Table 3.15 Participant specifications in Study 2.

		Indonesian		German	
		Younger	**Older**	**Younger**	**Older**
1	Number of participants	15 (8 female, 7 male)	15 (5 female, 10 male)	15 (9 female, 6 male)	15 (7 female, 8 male)
2	Ages (years old)	28.5±4.7	50.7±6.3	27.8±4.5	51.1±6.1
3	Education level	High school - master		High school - PhD	
4	Experience grade - Assembly - LEGO	 2.4 2.6	 2.3 2.2	 2.7 3.2	 2.3 2.2

The number of participants to use the eye-tracking system is 26 (respectively, 13 German participants and 13 Indonesian participants). This system is applied to the younger-age group of German and Indonesian participants. The data from 4 participants is not included in this additional study due to difficulties of system calibration as well as inaccurate records of their eye movements.

The participants' assignments are: predicting the position of the next expected brick or carburetor part; assessing the task load and dissatisfaction grade; and determining the strategy of the assembly sequences.

Hypotheses

The following null hypotheses are formulated:

- The model of robot behavior (H_{01}), the assembly group (H_{02}), the cultural background of participants (H_{03}), and age of participant (H_{04}) do not significantly influence the prediction time.
- The model robot behavior (H_{05}), the assembly group (H_{06}), the cultural background of participants (H_{07}), and the age of participant (H_{08}) do not significantly influence the task load of participants.
- The model robot behavior (H_{09}), the assembly group (H_{10}), the cultural background of participants (H_{11}), and the age of participant (H_{12}) do not significantly influence the dissatisfaction grade of participants.
- The model robot behavior (H_{13}), the cultural background of participants (H_{14}), and the age of participant (H_{15}) do not significantly influence the subjective evaluation of assembly strategy.
- The model robot behavior (H_{16}), the assembly group (H_{17}), the cultural background of participants (H_{18}), and the area of interest (H_{19}) do not significantly influence the fixation duration in each AOI during the prediction task completion.

The data normality is tested by using the Kolmogorov-Smirnov test, whereas the homogeneity of variance is examined using Levene's test. An ANOVA is used to test hypotheses H_{01}, H_{02}, H_{03}, H_{04}, H_{05}, H_{06}, H_{07}, H_{08}, H_{09}, H_{10}, H_{11}, H_{12}, H_{16}, H_{17}, H_{18}, and H_{19}. The Cochran and McNemar test is used to test hypothesis H_{13}, H_{14}, and H_{15}. The significance level is set at α=0.05 for the all tests. The statistical analysis is separated between the product made from LEGO bricks and the carburetor to examine the influence of the independent variables.

3.2.2 Results

Prediction Time

The normality test for the prediction time has not shown significant deviation (*p = 0.139* for the product made from LEGO bricks and *p = 0.065* the carburetor). The homogeneity variance test has not shown significant differences (*p = 0.069* for the product made from LEGO bricks and *p = 0.328* for the carburetor). The examinations to establish whether significant differences between independent variables exist are performed by using the ANOVA. Table 3.16 shows the results of ANOVA for the prediction times for the products made from LEGO bricks (a) and the carburetor (b) products in Study 2.

According to the ANOVA in Table 3.16, the model of robot behavior *(p = 0.005)* and the age of participant *(p = 0.001)* for LEGO product indicate significant differences due to *p-values* less than 0.05. Based on these results, H_{01} and H_{04} can be rejected. On the contrary, H_{02} and H_{03} are not rejected. Regarding the carburetor, the *p-values* of the model of robot behavior is less than 0.05 *(p ≤ 0.001)*. This result indicates that the corresponding null hypothesis (H_{01}) should be rejected, while H_{02}, H_{03} and H_{04} are not rejected.

Table 3.16 The results of ANOVA for the prediction time in the product made from LEGO bricks (a) and the carburetor (b) in study 2.

(a)

Source	Type III Sum of Squares	df	F	Sig.
culture	3035597.201	1	.184	.669
age	1.824E8	1	11.033	.001*
assmblGr	36368739.39	1	2.199	.139
model	1.789E8	2	5.410	.005*
culture * age	44891885.10	1	2.715	.100
culture * assmblGrL	8266982.000	1	.500	.480
culture * model	23652085.15	2	.715	.490
age * assmblGrL	189233.735	1	.011	.915
age * model	36165986.61	**2**	1.094	.336
assmblGrL * model	86102878.10	**2**	2.604	.076
culture * age * assmblGrL	17421539.54	1	1.054	.305
culture * age * model	8164650.047	2	.247	.781
culture * assmblGrL * model	25875171.41	2	.782	.458
age * assmblGrL * model	60036463.27	2	1.815	.164
culture * age * assmblGrL * model	1319582.110	2	.040	.961

*p<0.05

(b)

Source	Type III Sum of Squares	df	F	Sig.
culture	68116393.16	1	1.559	.213
age	19773544.40	1	.452	.502
assmblGrC	77766872.56	1	1.780	.183
model	8.08E8	2	9.250	.000*
culture * age	4982508.995	1	.114	.736
culture * assmblGrC	23152648.47	1	.530	.467
culture * model	61597172.16	2	.705	.495
age * assmblGrC	1.068E8	1	2.443	.119
age * model	1104908.356	2	.013	.987
assmblGrC * model	2.184E8	2	2.499	.084
culture * age * assmblGrC	35746025.11	1	.818	.336
culture * age * model	78088356.90	2	.893	.410
culture * assmblGrC * model	42834167.32	2	.490	.613
age * assmblGrC * model	8394139.175	2	.096	.908
culture * age * assmblGrC * model	2.555E8	2	2.924	.055

*p<0.05

- Model of Robot Behavior

A post hoc comparison based on the Bonferroni correction of prediction time for the product made from LEGO bricks is conducted for the model of robot behavior due to the finding of significant difference. Table 3.17 shows the pairwise comparisons of the robot behavior models, while Figure 3.28 depicts the error bar chart of the three different models of robot behavior.

Table 3.17 Results of the post hoc tests of the prediction time for the model of robot behavior in the product made from LEGO bricks (Study 2).

	Model 1	**Model 3**	**Model 4**
Model 1		1.000	.067
Model 3	1.000		.011*
Model 4	.067	.011*	

*p < 0.05

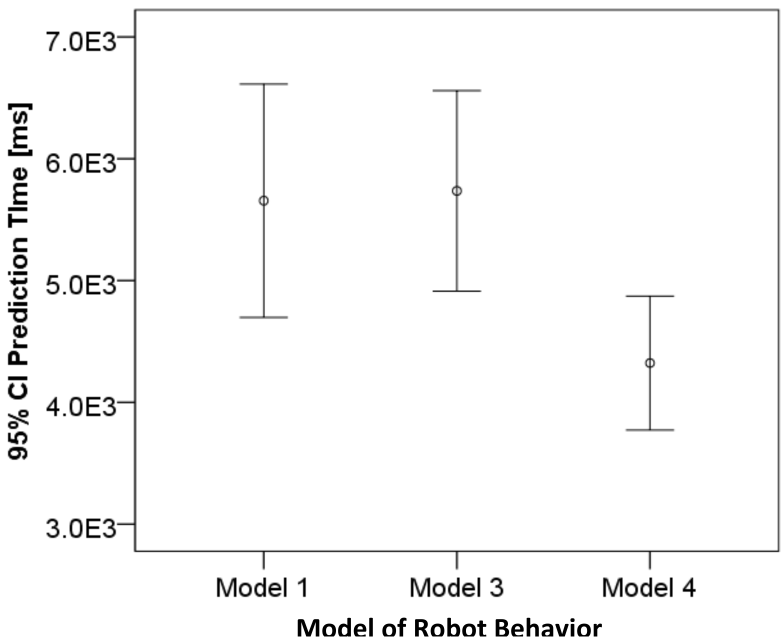


Figure 3.28. The error bar chart of the prediction time for the three different models of robot behavior in the product made from LEGO bricks (Study 2).

A comparison of the prediction times between Model 3 and Model 4 indicate a significant difference *(p = 0.011)*. Other comparisons have not shown any significant differences due to the post hoc test result (Table 3.17). Figure 3.28 shows that Model 4 – as the most human-oriented model – leads to the shortest time consumption for performing a correct prediction, while Model 3 reveals the longest prediction times.

The post hoc test regarding prediction times using the carburetor is performed for the model of robot behavior. Table 3.18 presents the pairwise comparisons of the robot behavior models, while Figure 3.29 shows the error bar chart.

Table 3.18 Results of the post hoc tests of the prediction time for the models of robot behavior in the carburetor (Study 2).

	Model 1	**Model 3**	**Model 4**
Model 1		.097	.032*
Model 3	.097		.001*
Model 4	.032*	.001*	

*p < 0.05

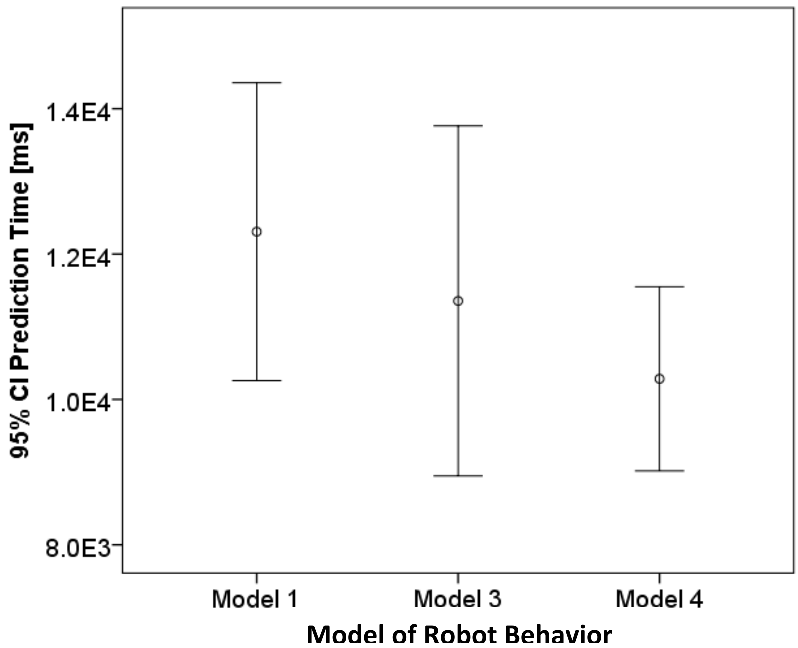


Figure 3.29 The error bar chart of the prediction times for the three different models of robot behavior with the carburetor (Study 2).

Based on Table 3.18, comparisons in prediction times between Model 3 and Model 4 ($p = 0.001$) as well as between Model 1 and Model 4 ($p = 0.032$) indicate a significant difference, while the comparison between Model 1 and Model 3 indicates insignificant differences.

The pairwise comparisons for both the product made from LEGO bricks and the carburetor show significant differences in comparisons between Model 4 and Model 3.

- Age Differences

According to the ANOVA in Table 3.19, a comparison of the ages of participants *($p = 0.001$)* with the product made from LEGO bricks indicates a significant difference due to *p-values* less than 0.05. The result of the pairwise comparison based on a Bonferroni correction for participant age is shown in Table 3.19. Figure 3.30 depicts the error bar chart of the prediction times depending on participant age for the product made from LEGO bricks.

Table 3.19 Results of the post hoc test of the prediction times regarding participants' ages with the product made from LEGO bricks (Study 2).

	Younger	Older
Younger		0.002*
Older	0.002*	

*p < 0.05

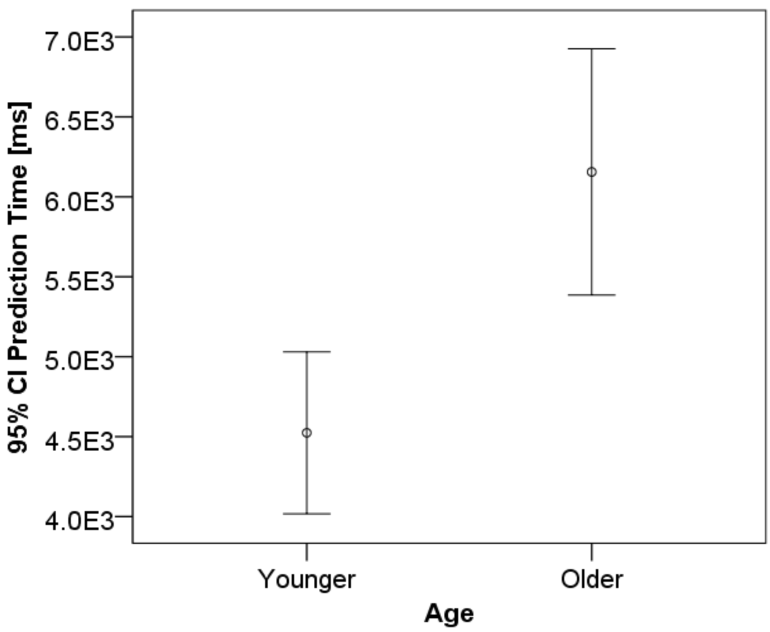


Figure 3.30. The error bar chart of the prediction times for the two different age groups with the product made from LEGO bricks (Study 2).

Based on the Bonferroni post hoc test (Table 3.19), the comparison between the younger and older groups shows a significant difference (*$p = 0.002$*). The younger group also achieve a shorter prediction time than the older group.

The analysis regarding age has not shown significant difference for the carburetor (*$p = 0.502$)*. Thus, no further statistical analysis is performed. A descriptive statistical analysis is conducted to inform the differences in prediction times based on age as shown in Figure 3.31. The results show that the prediction times of the younger group (mean = 12131.160 ms, SD = 8208.862 ms) are lower than those of older group (mean = 12544.500 ms, SD = 7037.872 ms).

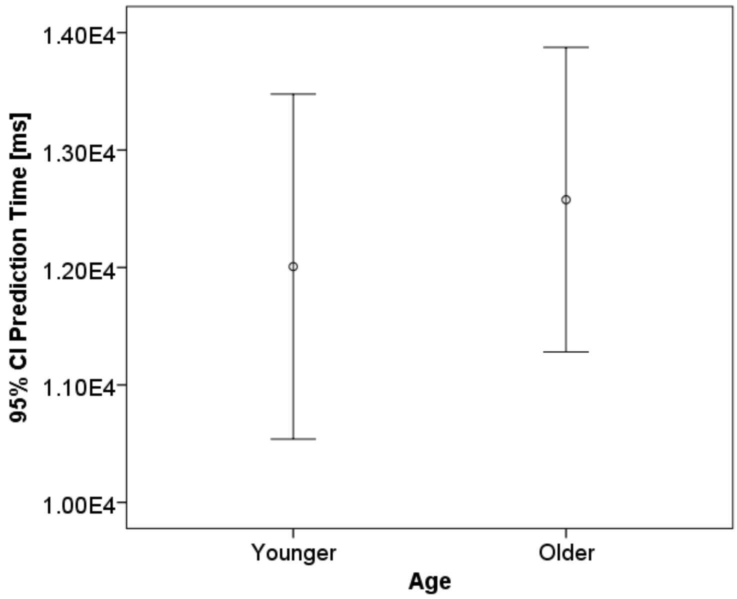


Figure 3.31. The error bar chart of the prediction times for the two different age groups with the carburetor (Study 2).

- Cultural Differences

Based on the ANOVA, the prediction times have not shown any significant differences with regard to culture (*p = 0.669* for the product made from LEGO bricks and *p = 0.213* for the carburetor). The descriptive statistical analyses are conducted to examine the prediction time based on the culture variable. Figure 3.32 shows the prediction time for the product made from LEGO bricks, while Figure 3.33 describes the prediction times for the carburetor. Figure 3.32 shows that the prediction times of the Indonesian participants (mean = 5439.696 ms, SD = 4652.177 ms) is higher than the German participants (mean = 5308.663 ms, SD = 3894.143 ms) when using the product made from LEGO bricks.

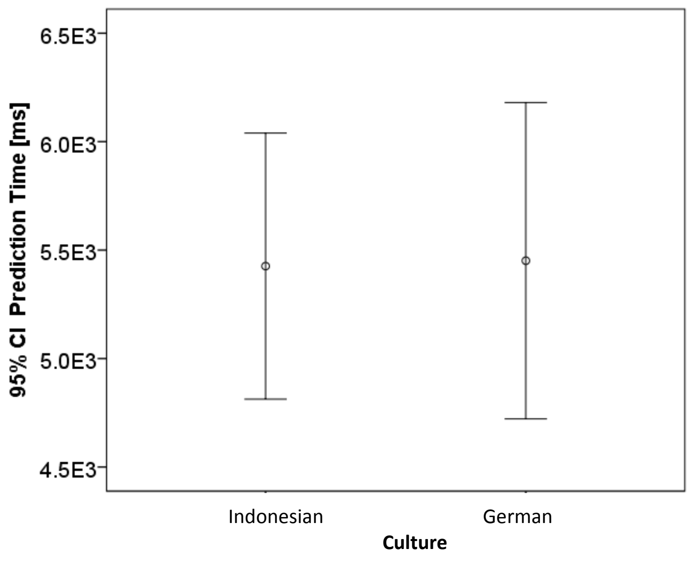


Figure 3.32. The error bar chart of the prediction times of the two different cultures in the product made from LEGO bricks (Study 2).

Similarly, Figure 3.33 shows that the prediction times of Indonesian participants (mean = 12562.750 ms, SD = 8824.386 ms) are higher than German participants (mean = 12077.080 ms, SD = 6192.674 ms) using the carburetor.

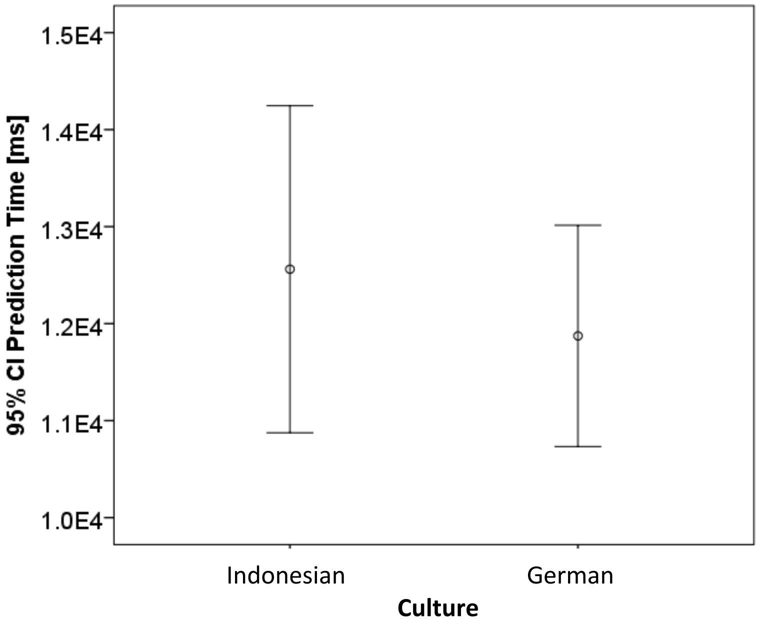


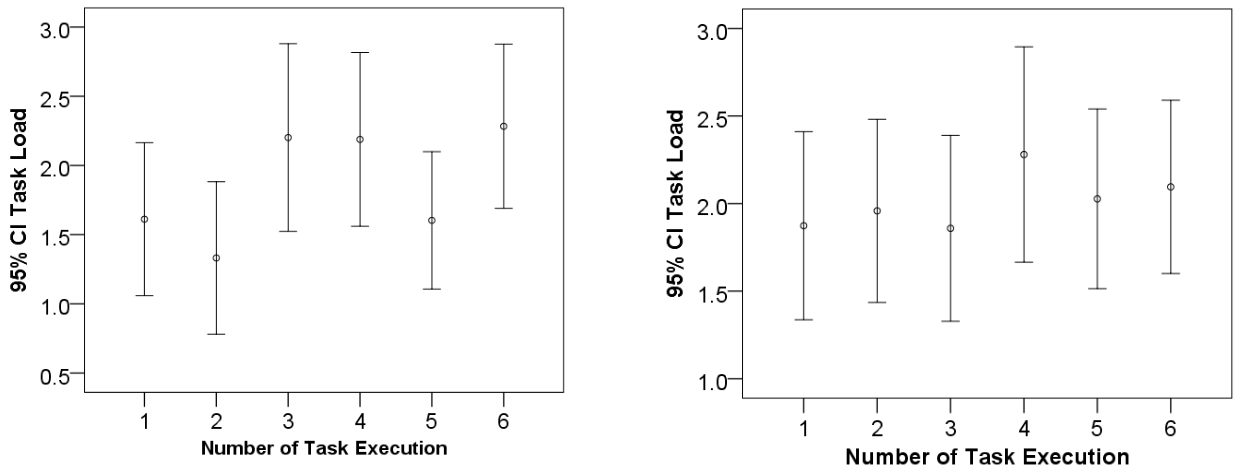
Figure 3.33. The error bar chart of the prediction times for the two culture groups with the carburetor (Study 2).

Subjective Evaluation

- Task load

The results of statistical analysis of the task load show normal distributions (*p = 1.000* for both the product made of LEGO bricks and the carburetor) and homogeneity of variances (*p = 0.502* for the product made of LEGO bricks and *p = 0.477* for the carburetor) in Study 2. The ANOVA is performed to examine the task load based on the chronological analysis and the independent variables as in Study 1.

According to the ANOVA results, there is a significance difference in the task load for the product made from LEGO bricks chronologically ($p \leq 0.001$), while an insignificant difference is found in the task load for the carburetor (p = 0.070). Figure 3.34 shows the error bar chart of the task load of the product made from LEGO bricks (a) and the carburetor (b) chronologically.



(a) (b)

Figure 3.34 Chronological error bar chart of the task load for the product made from LEGO bricks (a) and the carburetor (b) in Study 2.

To analyze the differences between the independent variables and their interaction, an ANOVA is conducted. Table 3.20 shows the ANOVA results for the task load of the product made from LEGO bricks (a) and the carburetor (b) depending on the dependent variables.

Based on the ANOVA (see Table 3.20), there is a significant difference in the task load for the product made from LEGO bricks regarding culture *($p \leq 0.001$),* age ($p = 0.005$) and the model of robot behavior ($p = 0.018$) variables. However, there is an interaction between culture and age ($p = 0.049$). Thus, further analysis on the main variables of culture, age and the model should not be performed. The post hoc test is performed to investigate the pairwise comparison of culture and age interaction. H_{06} *($p = 0.562$)* for the product made from LEGO bricks is also not rejected due to an insignificant difference (*p-value* > 0.05).

According to the ANOVA on the task load using the carburetor, H_{05} and H_{06} are not rejected regarding the finding of the insignificant difference in the models of robot behavior ($p = 0.929$) and assembly groups ($p = 0.160$). Significant differences are found for culture *($p \leq 0.001$)* and age ($p = 0.013$). Thus, H_{07} and H_{08} are rejected.

Table 3.20 The results of ANOVA for the task load in the product made from LEGO bricks (a) and the carburetor (b) (Study 2)

(a)

Source	Type III Sum of Squares	df	F	Sig.
culture	252.004	1	56.855	.000*
age	35.469	1	8.002	.005*
model	36.199	2	4.084	.018*
assmblGrL	1.495	1	.337	.562
culture * age	17.336	1	3.911	.049*
culture * model	4.975	2	.561	.571
culture * assmblGrL	.054	1	.012	.912
age * model	3.388	2	.382	.683
age * assmblGrL	.413	1	.093	.760
model * assmblGrL	10.895	2	1.229	.294
culture * age * model	1.354	2	.153	.858
culture * age * assmblGrL	.003	1	.001	.980
culture * model * assmblGrL	2.668	2	.301	.740
age * model * assmblGrL	6.232	2	.703	.496
culture * age * model * assmblGrL	9.195	2	1.037	.356

$^*p < 0.05$

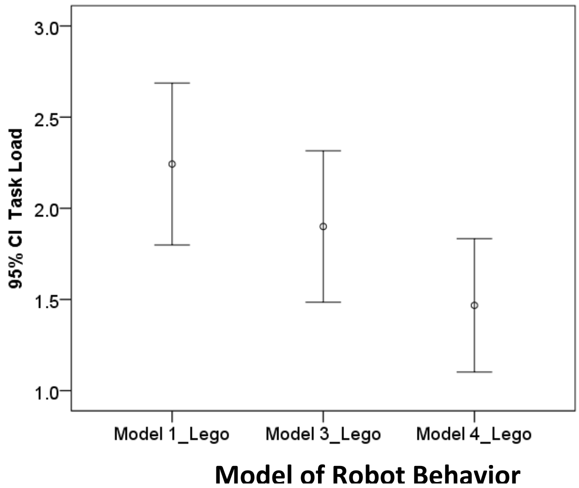
(b)

Source	Type III Sum of Squares	df	F	Sig.
culture	138.632	1	33.015	.000*
Age	25.921	1	6.173	.013*
assmblGrC	8.342	1	1.987	.160
model	.614	2	.073	.929
culture * age	12.100	1	2.882	.091
culture * assmblGrC	1.419	1	.338	.561
culture * model	1.028	2	.122	.885
age * assmblGrC	5.725	1	1.363	.244
age * model	.093	2	.011	.989
assmblGrC * model	.487	2	.058	.944
culture * age * assmblGrC	.348	1	.083	.773
culture * age * model	.267	2	.032	.969
culture * assmblGrC * model	4.782	2	.569	.566
age * assmblGrC * model	.254	2	.030	.970
culture * age * assmblGrC * model	.096	2	.011	.989

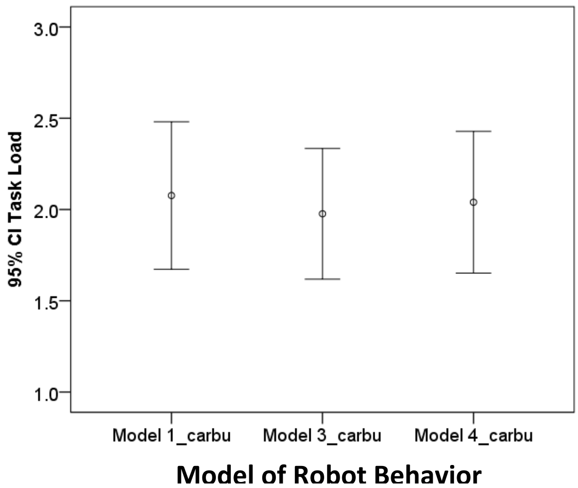
$^*p < 0.05$

- Model of Robot Behavior

Based on the ANOVA for the model of robot behavior, a significant difference for the product made from LEGO bricks *(p = 0.018)* is found. The ANOVA has not shown a significant difference for the carburetor *(p = 0.929).* The further statistical analyses are not conducted for both products due to the finding of interaction between age and culture in the product made from LEGO bricks and the insignificant difference with the carburetor. Figure 3.35 shows the differences in the task load depending on the model of robot behavior for the product made from LEGO bricks (a) and the carburetor (b). The figures show that Model 4 leads to the lowest task load both for the product made from LEGO bricks (mean = 1.5, SD = 2.0) and the carburetor (mean = 2.0, SD = 2.0)



(a)



(b)

Figure 3.35 The error bar chart of the task load for the three different models of robot behavior for the product made from LEGO bricks (a) and the carburetor (b) in Study 2.

- Age Differences

Based on ANOVA results for the product made from LEGO bricks, a significant difference is found in the age variable. However, an interaction between age and culture is also indicated. Thus, a post hoc test is performed for this interaction.

For the carburetor product, ANOVA shows a significant difference in the age variable (*p = 0.013)*. Furthermore, a post hoc comparison using the carburetor is performed for the age variable. The T-test result for the task load depending on cultural background shows a significant difference between the Indonesian and the German participants (t(179) = 5.591, *p ≤ 0.001).* Figure 3.36 shows the error bar chart of task load for age in the product made from LEGO brick (a) and carburetor (b). The older groups (mean = 2.2, SD = 2.4 in the LEGO product and mean = 2.3, SD = 2.1 in the carburetor) perceive a higher task load than the younger group (mean = 1.6, SD = 2.1 for the LEGO product and mean = 1.8, SD = 2.1 for the carburetor).

Figure 3.36 The error bar chart of the task load regarding participants' ages with the LEGO product (a) and carburetor (b) (Study 2).

- Cultural Differences

The ANOVA results show significant differences in the culture variable, both for the LEGO and carburetor products. However, the post hoc test for the LEGO product is not conducted due to the findings of the interaction between age and culture variables. A pairwise test for culture is conducted only for the carburetor. The results of T-test show significant differences in the task load with the carburetor ($t(179) = -2.447$, $p = 0.015$). Figure 3.37 shows the error bar chart of the task load regarding culture with the product made from LEGO bricks (a) and the carburetor (b).

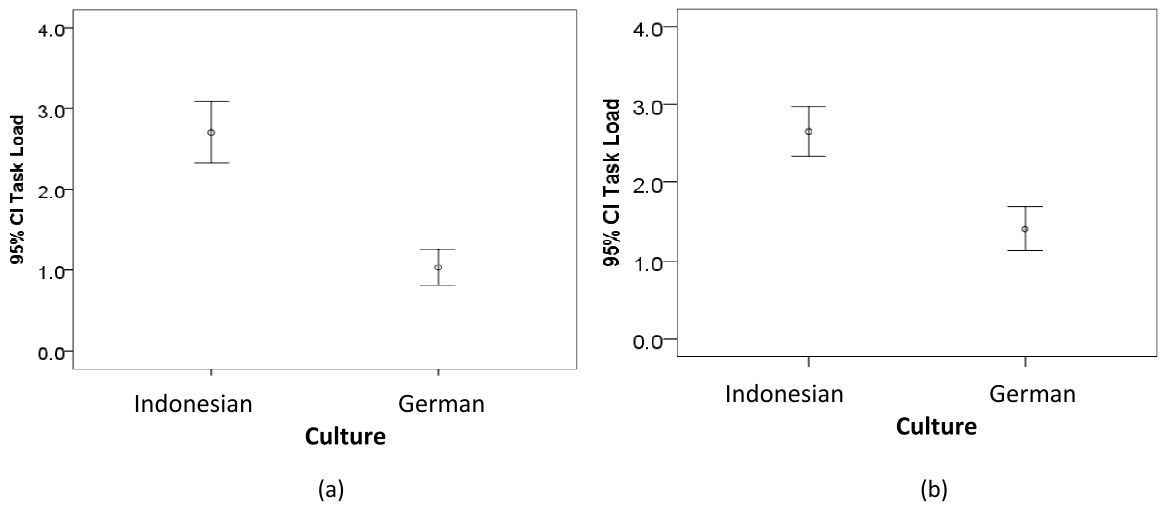


Figure 3.37 The error bar chart of the task load regarding culture with the LEGO product (a) and carburetor (Study 2).

Figure 3.37 show that the Indonesian participants (mean = 2.7, SD = 2.6 with the LEGO product and mean = 2.7, SD = 2.5 with the carburetor) receive higher task load than the German participants (mean = 1.0, SD = 1.4 with the LEGO product and mean = 1.4, SD = 1.9 with the carburetor).

A post hoc test based on the Bonferroni correction is performed to test the interaction between age and culture using the product made from LEGO bricks. Table 3.21 presents the pairwise comparisons of age and culture, while Figure 3.38 describes the plot graphic of the task load based on the interaction between culture and age.

Table 3.21 Results of the post hoc test result of task load regarding the culture and age interaction with the product made from LEGO bricks (Study 2).

		Older	**Younger**
German	**Older**		.548
	Younger	.548	
Indonesian	**Older**		.001*
	Younger	.001*	

*p < 0.05

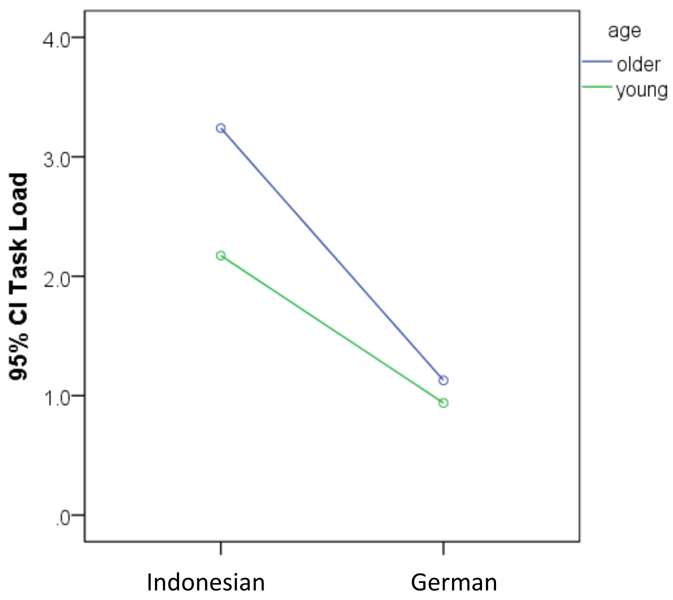
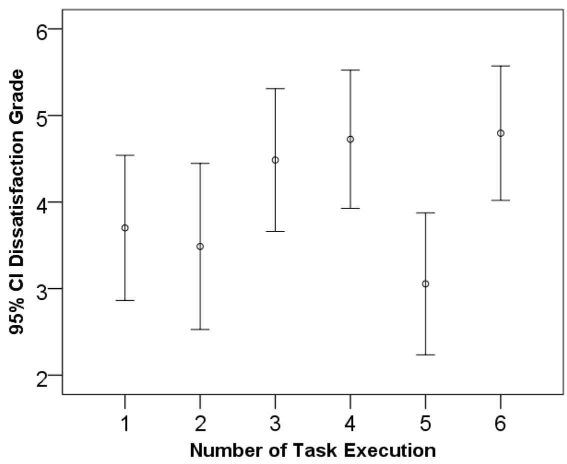


Figure 3.38 The interaction plot of the culture and age variables for task load with the product made from LEGO bricks (Study 2).

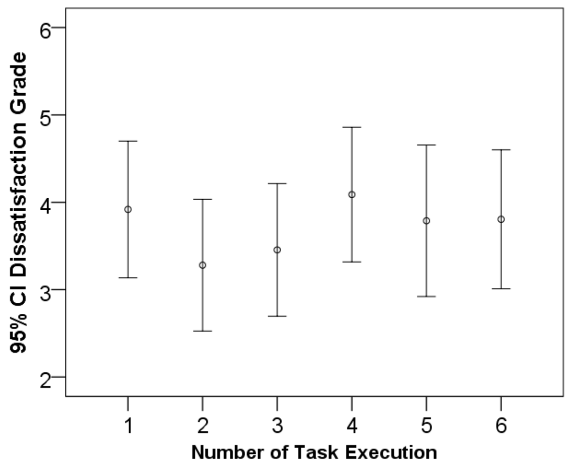
- Dissatisfaction Grade

The normality distribution test for dissatisfaction grades during Study 2 defines normal distributions both for the product made from LEGO bricks and the carburetor ($p = 1.000$). The homogeneity of variance tests with the Levene's test have also not shown significant deviations ($p = 0.504$ with the product made from LEGO bricks and $p = 0.377$ the carburetor). The ANOVA is statistically conducted to investigate the dissatisfaction grade of participants concerning the assembly sequence performance. The analysis is processed based on the chronological analysis and dependent and independent variables.

The ANOVA shows a significant difference in dissatisfaction grades over time for the product made from LEGO bricks ($p \leq 0.001$). The dissatisfaction grade for the carburetor has not shown significant differences ($p = 0.087$). Figure 3.39 depicts the error bar chart of the dissatisfaction grade with the product made from LEGO bricks (a) and the carburetor (b) chronologically.



(a)



(b)

Figure 3.39 Chronologically error bar chart of the dissatisfaction grade for the product made from LEGO bricks (a) and the carburetor (b) in Study 2.

The ANOVA of the dissatisfaction grade is statistically carried out to observe the independent variables of the dissatisfaction grade during task completion. Table 3.22 describes the detailed ANOVA result on the dissatisfaction grades for the product made from LEGO bricks (a) and the carburetor in Study 2.

Significant differences for the model, culture, and age variables ($p < 0.05$) are detected based on the ANOVA for the product made from LEGO bricks. A significant difference is also found in the interaction between culture and age ($p = 0.041$). Thus, all hypotheses (H_{09}, H_{10}, H_{11}, and H_{12}) are not rejected, and the Bonferroni post hoc test is conducted for the culture and age interaction.

There is also significant difference regarding culture *($p \leq 0.001$)* and age *($p = 0.034$)* for the carburetor. Hence, H_{11} and H_{12} are rejected, whereas H_{09} and H_{10} are not rejected. The pairwise comparisons of culture and the age with the carburetor are further analyzed.

Table 3.22 ANOVA results of dissatisfaction grades with the product made from LEGO bricks (a) and the carburetor (b) (Study 2).

(a)

Source	Type III Sum of Squares	df	F	Sig.
culture	148.832	1	15.363	.000*
age	47.029	1	4.854	.028*
assmblGrL	26.527	1	2.738	.099
model	140.923	2	7.273	.001*
culture * age	40.616	1	4.193	.041*
culture * assmblGrL	.340	1	.035	.852
culture * model	18.918	2	.976	.378
age * assmblGrL	10.914	1	1.1.27	.289
age * model	4.118	2	.213	.809
assmblGrL * model	11.396	2	.588	.556
culture * age * assmblGrL	4.056	1	.419	.518
culture * age * model	9.354	2	.483	.617
culture * assmblGrL * model	6.453	2	.333	.717
age * assmblGrL * model	11.782	2	.608	.545
culture * age * assmblGrL * model	50.657	2	2.615	.075

*p < 0.05

(b)

Source	Type III Sum of Squares	df	F	Sig.
culture	281.784	1	33.261	.000*
age	38.351	1	4.527	.034*
assmblGrC	.038	1	.004	.947
model	9.301	2	.549	.578
culture * age	30.567	1	3.608	.058
culture * assmblGrC	.756	1	.089	.765
culture * model	3.362	2	.198	.820
age * assmblGrC	1.560	1	.184	.668
age * model	1.305	2	.077	.926
assmblGrC * model	5.831	2	.344	.709
culture * age * assmblGrC	4.075	1	.481	.488
culture * age * model	.170	2	.010	.990
culture * assmblGrC * model	6.106	2	.360	.698
age * assmblGrC * model	4.765	2	.281	.755
culture * age * assmblGrC * model	6.423	2	.379	.685

*p < 0.05

- Model of Robot Behavior

Based on Table 3.22, there is a significant difference between results for the product made from LEGO bricks *(p = 0.001)* and an insignificant difference between results for the carburetor *(p = 0.578).* However, further statistical analysis is not performed due to the findings on the interaction between age and culture with the product made from LEGO bricks and the insignificant differences in results for the carburetor. Figure 3.40 shows the dissatisfaction grade depending on the model of robot behavior using the product made from LEGO bricks (a) and the carburetor (b).

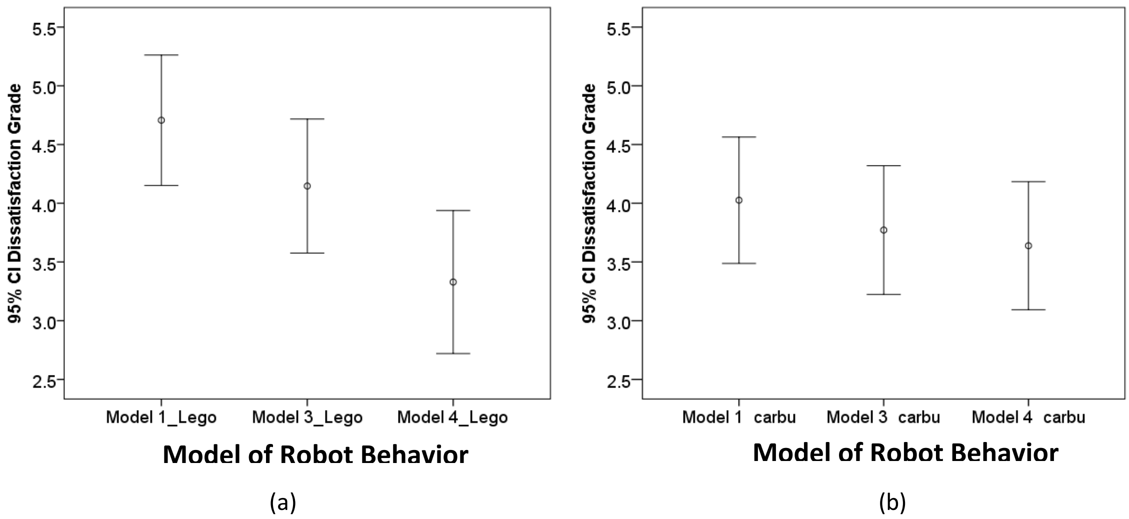


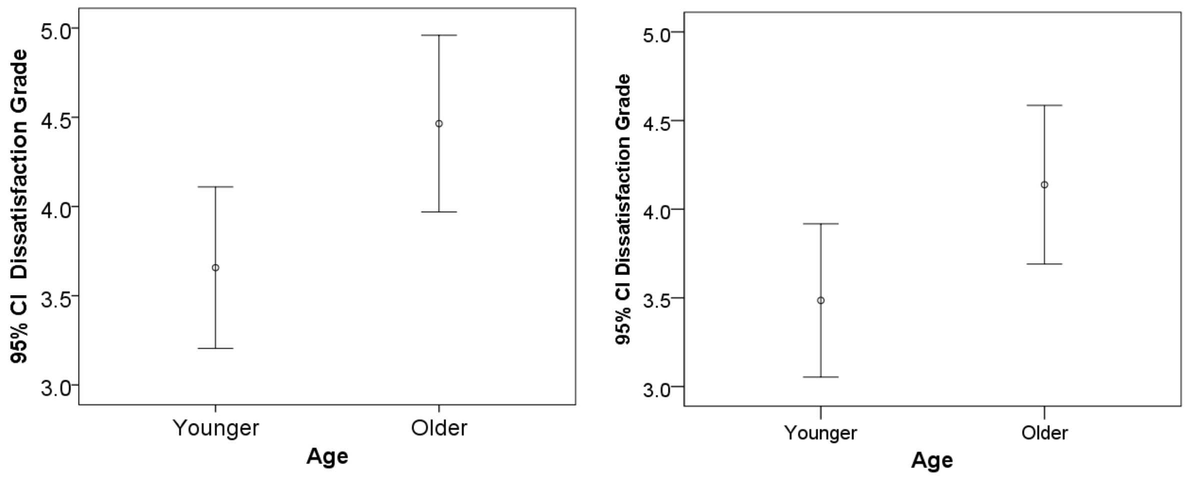
Figure 3.40 The error bar chart of the dissatisfaction grade for the three different models of robot behavior with the product made from LEGO bricks (a) and the carburetor (b) in Study 2.

Figure 3.40 clarifies that Model 4 leads to the lowest dissatisfaction grades (mean = 3.3, SD = 3.4 for the product made from LEGO bricks and mean grades = 3.6, SD = 3.0 for the carburetor). On the contrary, Model 1 results in the worst dissatisfaction grades (mean = 4.7, SD = 3.1 for the product made from LEGO bricks and mean grades = 4.0, SD = 3.0 for the carburetor).

- Age Differences

The ANOVA results of dissatisfaction grades for the products made from LEGO brick show a significant difference (*p = 0.028)* in the age variable. However, an interaction between age and culture is also found. Thus, post hoc test is performed for this interaction.

The ANOVA for the carburetor shows a significant difference regarding age (*p = 0.034)*. Furthermore, a post hoc comparison using the carburetor is conducted for the age variable. The T-test results for dissatisfaction grades according to age show a significant difference between the Indonesian and German participants (t(179) = -2.035, *p = 0.043).* Figure 3.41 shows the error bar chart of dissatisfaction grades regarding age with the product made from LEGO brick (a) and the carburetor (b). The older groups (mean = 4.5, SD = 3.4 in the LEGO product and mean = 4.1, SD = 3.0 in the carburetor) perceive a higher task load than the younger group (mean = 3.6, SD = 2.1 with the LEGO product and mean = 3.5, SD = 3.2 with the carburetor).

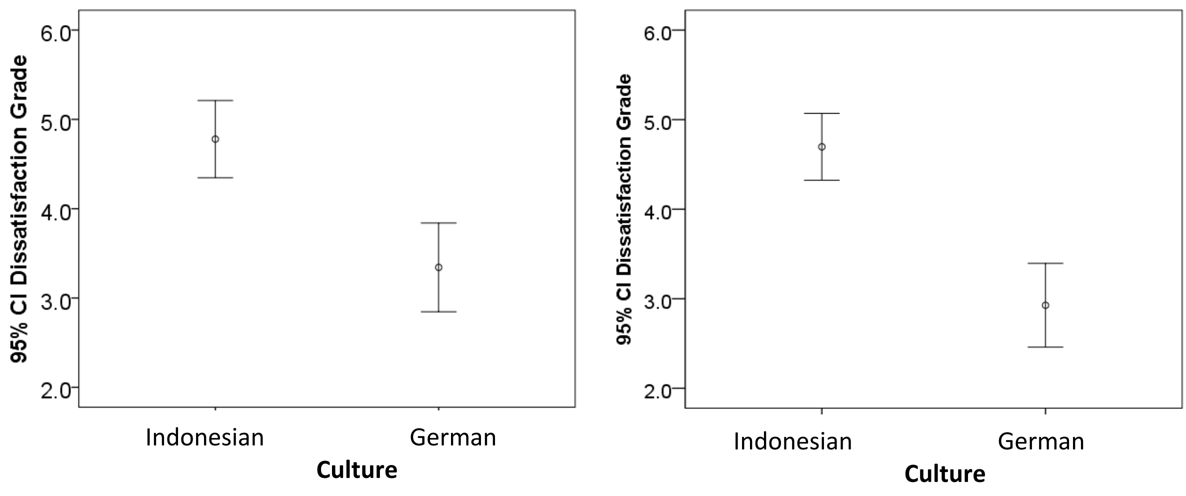


(a) (b)

Figure 3.41 The error bar chart of the dissatisfaction grades regarding age with the LEGO product (a) and carburetor (b) (Study 2).

- Cultural Differences

The ANOVA shows significant differences (*p ≤ 0.001)* regarding the culture variable for both the LEGO and carburetor products. However, the post hoc test for the LEGO product is not conducted due to the findings of the interaction between the age and culture variables. A pairwise test for culture is only conducted for the carburetor. The results of T-test show significant differences in dissatisfaction grades with the carburetor (t(179) = -2.035, *p ≤ 0.001)*. Figure 3.42 shows the error bar chart of the dissatisfaction grades regarding culture with the product made from LEGO brick (a) and the carburetor (b).



(a) (b)

Figure 3.42 The error bar chart of dissatisfaction grades regarding culture with the LEGO product (a) and the carburetor (Study 2).

Figure 3.42 show that the dissatisfaction grades of Indonesian participants (mean = 4.8, SD = 3.0 with the LEGO product and mean grades = 4.7, SD = 2.5 with the carburetor) perceive a higher task load than the German participants (mean = 3.3, SD = 3.4 with the LEGO product and mean = 3.0, SD = 3.2 with the carburetor).

A pairwise comparison is conducted to investigate the interaction between age and culture using the product made from LEGO bricks as shown in Table 3.23. Figure 3.43 illustrates the interaction between culture and age for dissatisfaction with the product made from LEGO bricks during Study 2.

Table 3.23 The post hoc test result of the dissatisfaction grade for the culture and age interaction with the product made from LEGO bricks (Study 2).

		Older	Younger
German	**Older**		.913
	Younger	.913	
Indonesian	**Older**		.003*
	Younger	.003*	

*p < 0.05

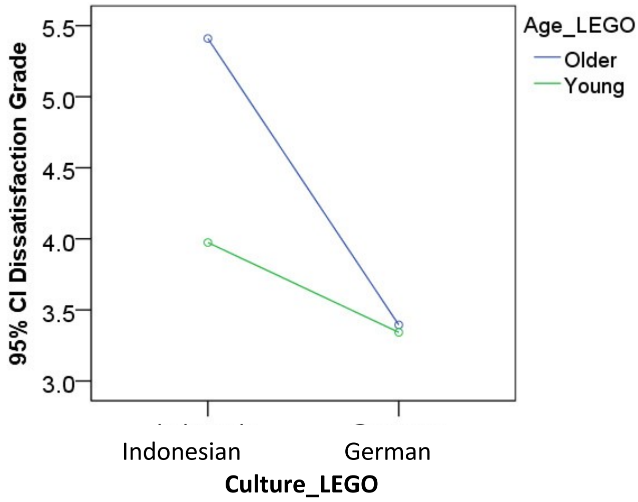


Figure 3.43 The interaction plot of dissatisfaction grades between age and culture with the product made from LEGO bricks (Study 2).

Dissatisfaction grades from Indonesian participants show significant differences between older and younger participants (*p = 0.003).* With regard to German participants, there is no significant difference between the younger and older groups (*p = 0.913).*

- Assembly Strategy Evaluation

With the intention of evaluating assembly strategy subjectively, participants are asked to give their opinion of whether a strategy is used in each assembly task. The subjective data is analyzed by means of Cochran's Q Test and a McNemar test regarding independent variables including model of robot behavior, age and the culture.

- Model of Robot Behavior

Based on the Cochran's Q test results, there are significant differences between the models of robot behavior ($\chi^2(2) = 74.998$, $p \leq 0.001$ for the product made from LEGO bricks and $\chi^2(2) = 13.581$, $p \leq 0.001$ for the carburetor). This means that H_{13} is rejected. The pairwise comparisons using McNemar is then performed to evaluate assembly strategy patterns across the three models. Table 3.24 defines the results of the McNemar test for the model of robot behavior with the product made from LEGO bricks (a) and the carburetor (b).

Table 3.24 The pairwise comparison of the assembly strategy evaluation between the models of robot behavior with the product made from LEGO bricks (a) and the carburetor (b) (Study 2).

(a)

	Model 1	Model 3	Model 4
Model 1		.002*	.000*
Model 3	.002*		.000*
Model 4	.000*	.000*	

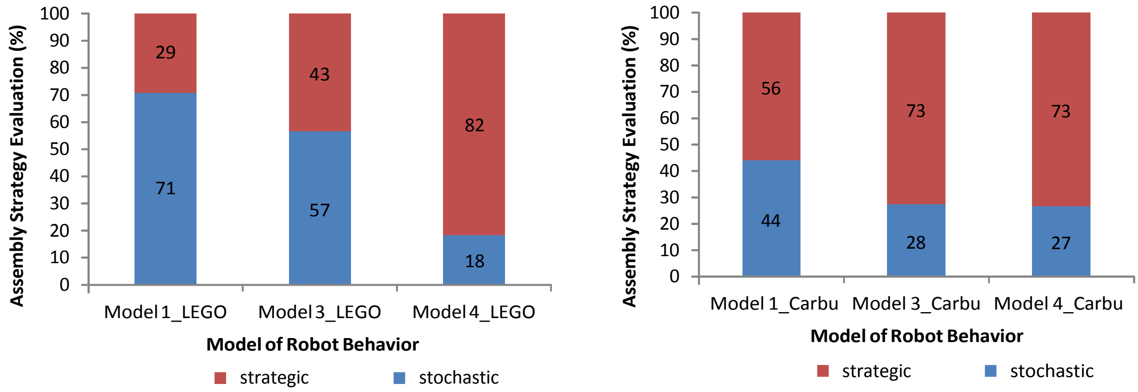
*p < 0.05

(b)

	Model 1	Model 3	Model 4
Model 1		.007*	.004*
Model 3	.007*		1.000
Model 4	.004*	1.000	

*p < 0.05

The results of the pairwise comparisons for the product made from LEGO bricks indicate significant differences ($p < 0.05$) for all interactions. Significant differences with the carburetor are shown in the interaction between Model 1 toward Model 3 ($p = 0.007$) and Model 4 ($p = 0.004$). Figure 3.44 depicts the assembly strategy evaluation based on the model of robot behavior in Study 2 for the product made from LEGO bricks (a) and the carburetor (b).

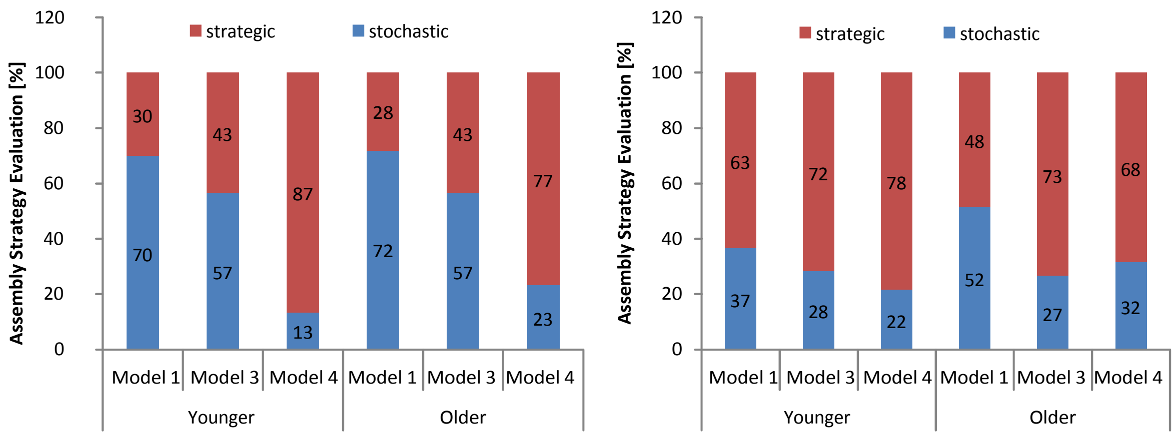


(a) (b)

Figure 3.44 The assembly strategy evaluation of the product made from LEGO bricks (a) and the carburetor (b) based on the model of robot behavior (Study 2).

- Age Differences

The Cochran's Q test has not shown significant difference between age groups. ($\chi^2(1) = 0.778$, $p = 0.378$ for the product made from LEGO bricks and $\chi^2(1) = 2.579$, $p = 0.108$ for the carburetor). This means that no further statistical analysis is conducted and the corresponding null hypothesis (H_{14}) is not rejected. Figure 3.45 shows the descriptive analysis of the assembly strategy evaluation regarding participant age for the product made from LEGO bricks (a) and the carburetor (b).



(a) (b)

Figure 3.45 The assembly strategy evaluation of the product made from LEGO bricks (a) and the carburetor (b) based on age (Study 2).

- Cultural Differences

According to the Cochran's test, insignificant differences are also found in the assembly strategy evaluation based on culture ($\chi^2(1) = 2.123$, $p = 0.145$ for the product made from LEGO bricks and $\chi^2(1) = 3.282$, $p = 0.170$ for the carburetor). Thus, H_{15} is not rejected. The descriptive statistic is formulated to show the differences in assembly strategy evaluation based on culture as shown in Figure 3.46.

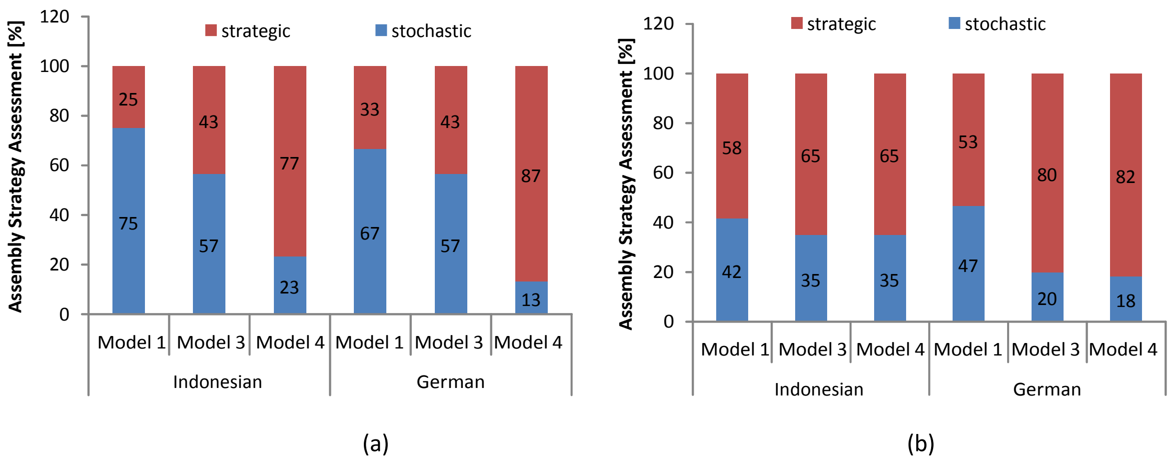


Figure 3.46 The assembly strategy evaluation of the product made from LEGO bricks (a) and the carburetor (b) based on culture (Study 2).

Area of Interest (AOI)

The eye-tracking system is utilized in Study 2 to measure the area of interest during task execution. The AOI are obtained based on the video data recorded during an assembly task. The eye focus and heat map analyses are utilized to analyze the eye movement and the fixation duration of each AOI for each participant. The eye tracking system is only used with the younger German and Indonesian participants. In total, there are 26 participants (13 German participants and 13 Indonesian participants) in the study with the eye-tracking system.

A statistical analysis using an ANOVA is conducted due to normal distribution in the fixation duration data ($p = 0.221$ for the product made from LEGO bricks and $p = 0.157$ for the carburetor) and the homogeneity of variances ($p = 0.913$ for the product made from LEGO bricks and $p = 0.201$ for the carburetor). Table 3.25 shows the result of the ANOVA for the fixation duration with the product made from LEGO bricks (a) and the carburetor (b).

According to the ANOVA of the fixation duration with the product made from LEGO bricks, the model of robot behavior, the assembly group and the AOI have *p-value* ≤ 0.001, while culture has not shown to make a significant difference ($p = 0.922$). However, there are interactions between the independent variables detected in ANOVA results. The ANOVA indicate significant differences in the interaction between the model of robot behavior and the assembly group ($p = 0.003$), and between the assembly group and the AOI ($p = 0.018$). Furthermore, a post hoc test should be conducted for the interactions only. Based on these facts, hypotheses H_{16}, H_{17}, H_{18} and H_{19} are not rejected.

With the carburetor, the model of robot behavior and the AOI are variables that indicate a significant difference ($p \leq 0.001$). However, an interaction between the model of robot behavior and the AOI is found ($p = 0.029$). Hypotheses H_{14}, H_{15}, H_{16} and H_{17} for the carburetor are also not rejected.

Table 3.25 The results of ANOVA for the fixation duration in the product made from LEGO bricks (a) and the carburetor (b) (study 2).

(a)

Source	Type III Sum of Squares	df	F	Sig.
culture	134618.403	1	.010	.922
model	4.781E8	2	17.204	.000*
assmblGrL	2.265E8	1	16.299	.000*
AOI	7.936E10	3	1903.889	.000*
culture * model	4505750.810	2	.162	.850
culture * assmblGrL	8277536.667	1	.596	.440
culture * AOI	69026684.49	3	1.656	.175
model * assmblGrL	1.664E8	2	5.990	.003*
model * AOI	1.227E8	6	1.472	.185
assmblGrL * AOI	1.409E8	3	3.380	.018*
culture * model * assmblGrL	17456651.83	2	.628	.534
culture * model * AOI	80151268.19	6	.961	.451
culture * assmblGrL * AOI	29215371.33	3	.701	.552
model * assmblGrL * AOI	1.676E8	6	2.010	.062
culture * model * assmblGrL * AOI	1.323E8	6	1.586	.148

$p < 0.05$

(b)

Source	Type III Sum of Squares	df	F	Sig.
culture	65125.662	1	.003	.955
model	4.706E8	2	11.738	.000*
AOI	6.559E10	3	1090.563	.000*
assmblGr_C	12784358.15	1	.638	.425
culture * model	2594850.874	2	.065	.937
culture * AOI	47121691.32	3	.784	.503
culture * assmblGr_C	23989267.87	1	1.197	.274
model * AOI	2.838E8	6	2.360	.029*
model * assmblGrL_C	1.025E8	2	2.558	.078
AOI*assmblGr_C	95650464.99	3	1.590	.190
culture * model * AOI	1.453E8	6	1.208	.300
culture * model * assmblGr_C	36375701.74	2	.907	.404
culture * AOI * assmblGr_C	1.201E8	3	1.998	.113
model * AOI * assmblGr_C	97786000.05	6	.813	.560
culture * model * AOI * assmblGr_C	41538844.70	6	.345	.913

$p < 0.05$

- Model of Robot Behavior

A pairwise comparison is conducted to show the interaction between the model of robot behavior and the assembly group with the product made from LEGO bricks as shown in Table 3.26. Figure 3.47 describes the interaction plot between the model of robot behavior and the assembly group for fixation duration in Study 2.

Table 3.26 Results from the post hoc test of the model of robot behavior and assembly group interaction for fixation duration with the product made from LEGO bricks (Study 2).

		Model 1	Model 3	Model 4
Pyramid	**Model 1**		.000*	.275
	Model 3	.000*		.000*
	Model 4	.275	.000*	
Ship	**Model 1**		.360	.365
	Model 3	.360		.069
	Model 4	.365	.069	

*p < 0.05

Significant differences ($p < 0.05$) are detected in comparisons between Model 1 and Model 3 as well as between Model 3 and Model 4 in pyramid interim state. The human assembly behavior in Model 4 also defines the shortest fixation duration with both the pyramid interim state and the ship interim state as shown in Figure 3.47.

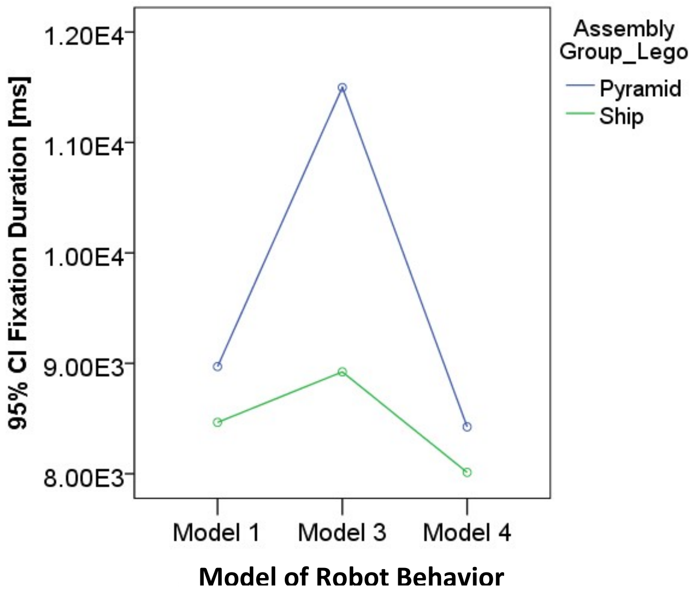


Figure 3.47 The interaction plot of the robot behavior model and assembly group for the fixation duration in the product made from LEGO bricks (Study 2).

The Bonferroni post hoc comparison is performed on the interaction between the model of robot behavior and the AOI using the carburetor as shown in Table 3.27, and plotted in Figure 3.48. Figure 3.48 describes that Model 4 leads to the shortest fixation duration for all AOI. Table 3.27

indicates significant differences with comparisons between Model 1 and Model 4 in AOI 1, AOI 2 and AOI 3, while AOI 4 has not shown significant differences for all comparisons.

Table 3.27 Results of the post hoc test on the interaction between the model of robot behavior and the AOI for fixation duration with the carburetor (Study 2).

		Model 1	Model 3	Model 4
AOI 1	**Model 1**		.055	.010*
	Model 3	.055		.529
	Model 4	.010*	.529	
AOI 2	**Model 1**		.770	.011*
	Model 3	.770		.025*
	Model 4	.011*	.025*	
AOI 3	**Model 1**		.000*	.000*
	Model 3	.000*		.613
	Model 4	.000*	.613	
AOI 4	**Model 1**		.783	.863
	Model 3	.783		.654
	Model 4	.863	.654	

*p < 0.05

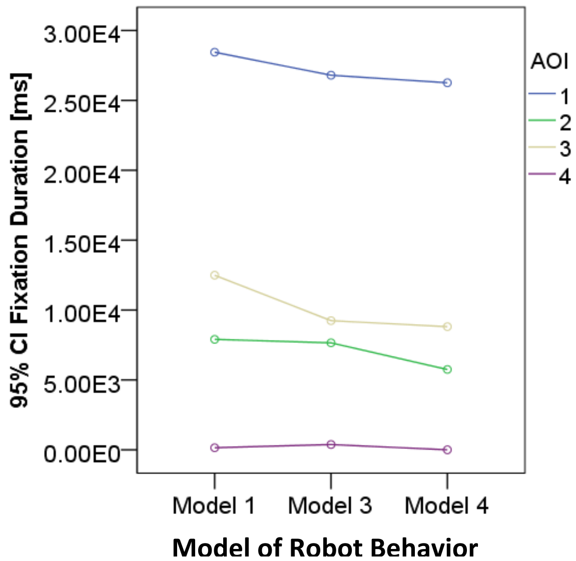
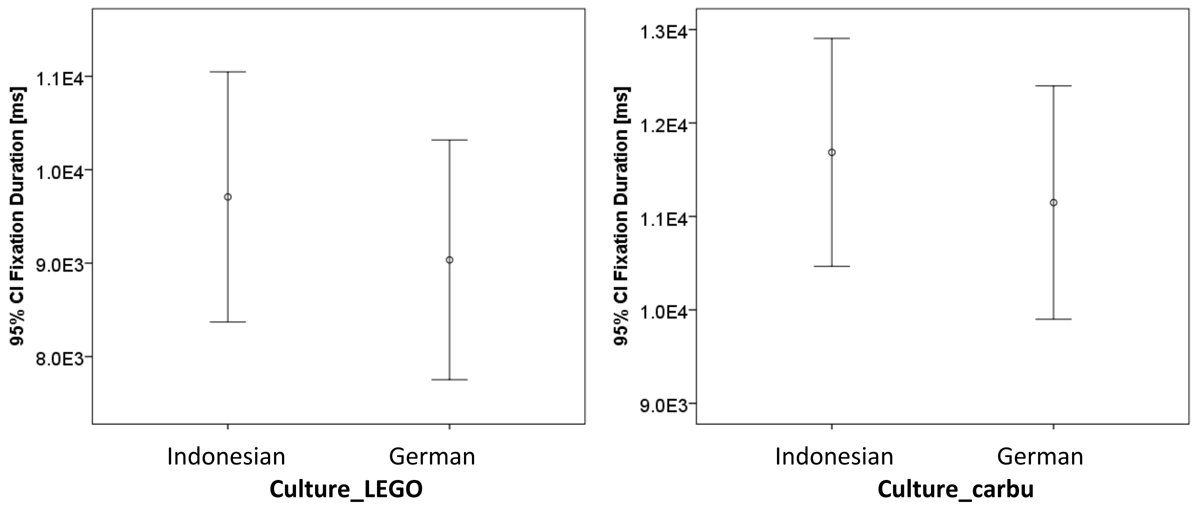


Figure 3.48 Interaction plot of the model of robot behavior and the AOI with the carburetor (Study 2)

- Cultural Differences

The ANOVA have not shown significant differences in fixation duration regarding culture for either the product made from LEGO bricks *(p = 0.922)* or the carburetor *(p = 0.955).* Thus, further statistical analyses are not performed. Descriptive analyses are conducted to show the differences in fixation duration based on the culture. Figure 3.49 describes the error bar chart of fixation duration regarding culture with the product made from LEGO bricks (a) and the carburetor (b).



(a) (b)

Figure 3.49 The error bar chart of fixation durations for the two different culture groups with the product made from LEGO bricks (a) and the carburetor (b) (Study 2).

Figure 3.49 clarifies that the Indonesian participants require a longer fixation duration (mean = 9987.894 ms, SD = 11616.562 ms) than the German participants (9034.795 ms, SD = 11514.510 ms) when using the product made from LEGO bricks. Similarly, with the carburetor, the Indonesian participants require a longer fixation duration (mean = 11148.205 ms, SD = 11209.169 ms) than the German participants (mean = 11028.583 ms, SD = 10646.550.562 ms)

- Assembly Group and AOI interaction

As shown in ANOVA results, there is an interaction between the assembly group and the AOI. Thus, a post hoc comparison is conducted based on the Bonferroni correction. Table 3.28 explains the pairwise comparisons between the assembly groups and the AOI in Study 2. Figure 3.50 plots the interaction between the assembly group and the AOI.

Table 3.28 Results of the post hoc test on assembly group and AOI interaction for fixation duration with the product made from LEGO bricks (Study 2).

		AOI1	AOI2	AOI3	AOI4
Pyramid	**AOI1**		.000*	.000*	.000*
	AOI2	.000*		.000*	.000*
	AOI3	.000*	.000*		.000*
	AOI4	.000*	.000*	.000*	
Ship	**AOI1**		.000*	.000*	.000*
	AOI2	.000*		.000*	.000*
	AOI3	.000*	.000*		.000*
	AOI4	.000*	.000	.000*	

*p < 0.05

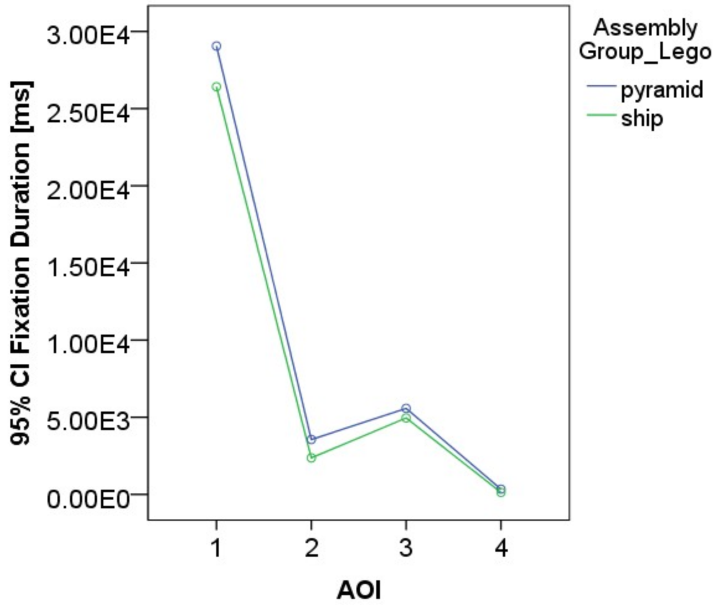


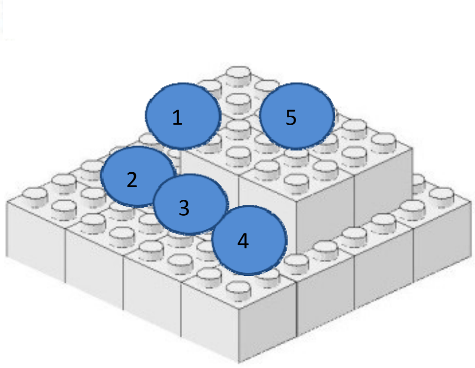
Figure 3.50 The interaction plot of the model of robot behavior and the AOI for fixation duration with the product made from LEGO bricks (Study 2).

Based on the post hoc test, significant differences ($p < 0.05$) are found in all interactions between the assembly group and the AOI. Model 4 leads to the shortest fixation duration for both the pyramid and the ship.

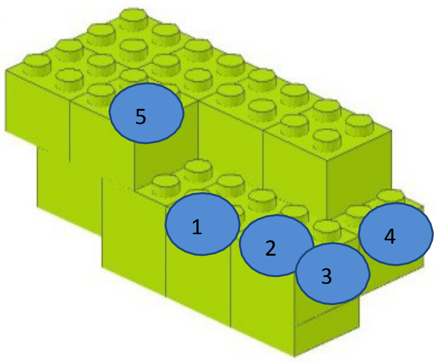
Position of Observed Part

For an advanced discussion, we consider the position of the predicted LEGO brick and the next carburetor part. The information is obtained based on a statistical analysis of the independent variables in Study 2.

There are five possibilities of predicted brick position for the pyramid and ship interim states. Those possibilities are also present in the carburetor 2 interim state, while the carburetor 1 interim state has six possible positions of the expected part. Every model of robot behavior results in a different position possibility. For example, Model 4, which most accurately represents human behavior, predicts only one position of the brick and carburetor part, while Model 1, with no human-oriented assembly rules, predicts an equal distribution of five position possibilities (or six for carburetor 1). Figure 3.51 shows the possibilities of the predicted brick and carburetor part position for each interim state.



(a)



(b)

(c)

(d)

Figure 3.51 The possibilities of the predicted brick and carburetor part positions for the pyramid (a), ship (b), carburetor 1 (c) and carburetor 2(d) interim states (Study 2).

Data on the predicted brick or part position is obtained and summarized for each age and culture group. Figure 3.52 depicts the expected and observed positions of the LEGO brick and the carburetor part for the younger Indonesian participants. Figure 3.53 shows the comparisons between the expected and observed bricks for the older Indonesian participants. The distribution of the observed and expected positions of brick and carburetor part for the younger German participants is described in Figure 3.54. Figure 3.55 describes the observed and expected positions of brick and carburetor parts for the older German participants in Study 2.

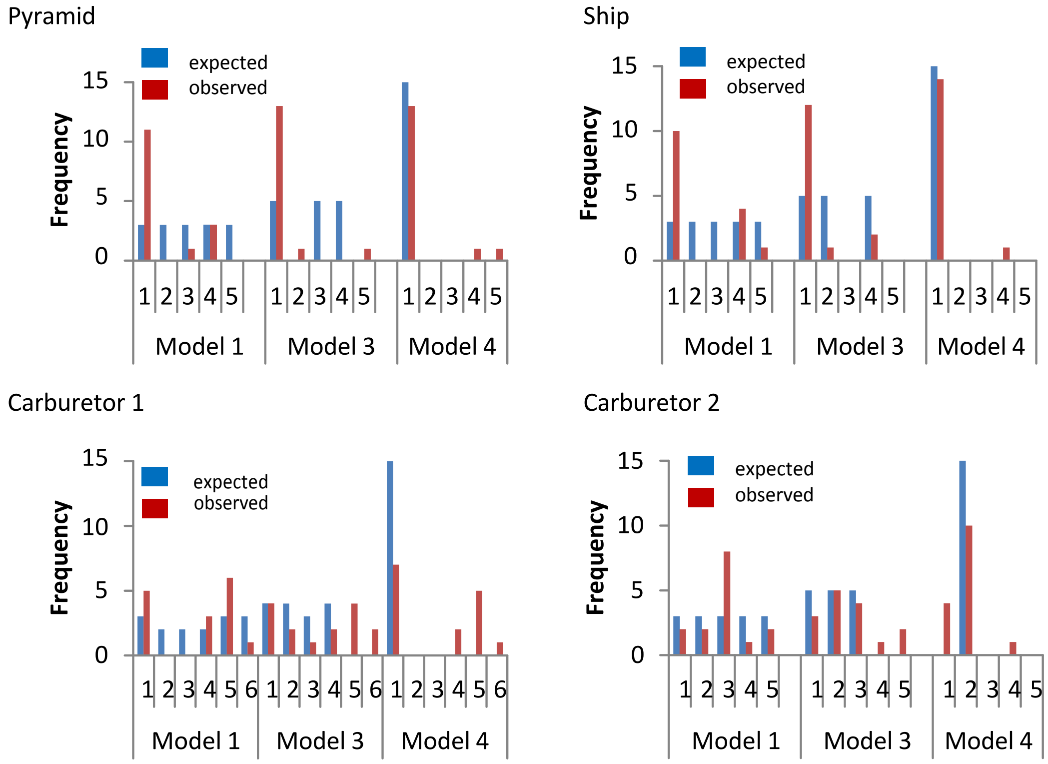


Figure 3.52 Distribution of the observed and expected positions of the brick and the carburetor part with younger Indonesian participants (Study 2).

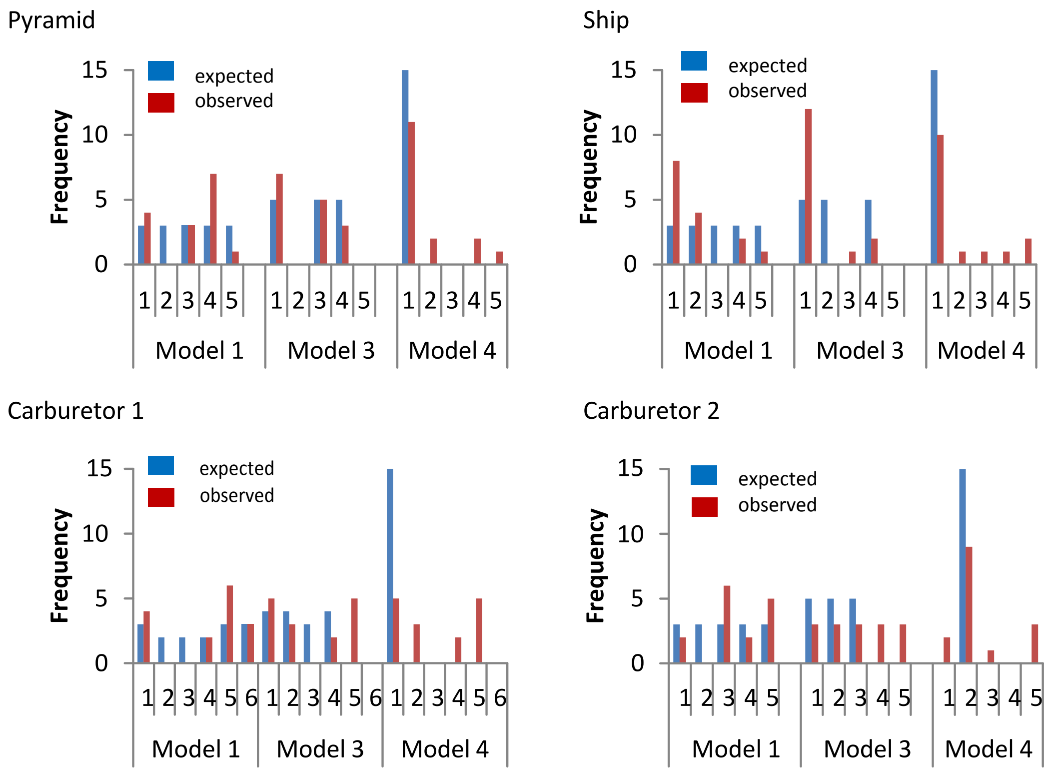


Figure 3.53 Distribution of the observed and expected positions of the brick and the carburetor part with older Indonesian participants (Study 2).

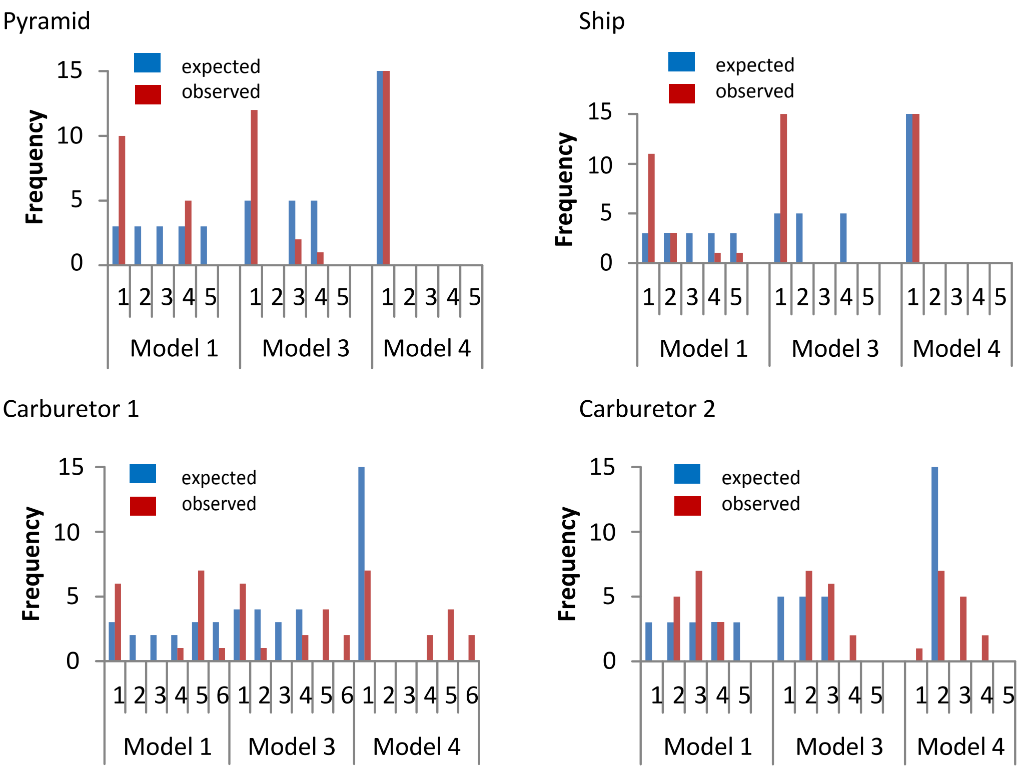


Figure 3.54 Distribution of the observed and expected positions of the brick and the carburetor part with younger German participants (Study 2).

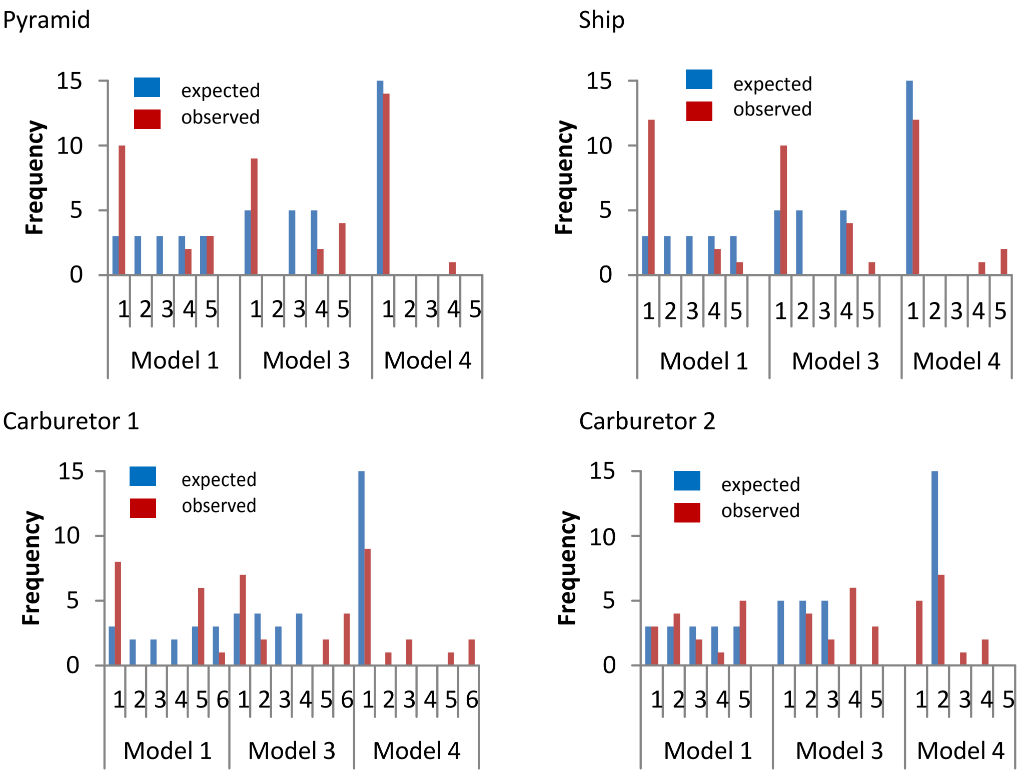


Figure 3.55 Distribution of the observed and expected positions of the brick and the carburetor part with older German participants (Study 2).

Summarizing the position data, Table 3.29 gives the percentages concerning either the LEGO brick or the carburetor part positions for each model of robot behavior and assembly group based on culture and age differences.

Table 3.29 Summary of the observed brick (a) and carburetor part (b) position (Study 2).

(a)

		Pyramid			Ship		
		Model 1	**Model 3**	**Model 4**	**Model 1**	**Model 3**	**Model 4**
Indonesian	**younger**	1 (73%)	1(87%)	1(87%)	1(67%)	1(80%)	1(93%)
	older	4(47%)	1(47%)	1(73%)	1(53%)	1(80%)	1(67%)
German	**younger**	1(67%)	1(80%)	1(100%)	1(73%)	1(100%)	1(100%)
	older	1(67%)	1(60%)	1(93%)	1(80%)	1(67%)	1(80%)

(b)

		Carburetor1			Carburetor2		
		Model 1	**Model 3**	**Model 4**	**Model 1**	**Model 3**	**Model 4**
Indonesian	**younger**	5(40%)	1, 5(27%)	1(80%)	3(53%)	2(33%)	2(67%)
	older	5(40%)	1, 5(33%)	1(67%)	3(40%)	1,2,3,4,5(20%	2(60%)
German	**younger**	1(40%), 5(47%)	1(40%)	1(73%)	2(47%)	2(47%), 3(40%)	2(47%)
	older	1(53%), 5(40%)	1(47%)	1(73%)	5(33%)	4(40%)	2(47%)

According to the brick positioning, it can be concluded that position 1 is the most preferred position for both the pyramid and the ship interim states. The selected position for the carburetor interim states varies depending on the model of robot behavior and the assembly group.

In addition, the predictive accuracy based on the distribution of the difference between the expected and the observed positions with regard to formula (3.1) is calculated. Table 3.30 shows the deviations in the predicted brick or carburetor part in Study 2.

Table 3.30 Deviation in the predicted brick (a) and carburetor part (b) position (Study 2).

(a)

		Pyramid			Ship		
		Model 1	**Model 3**	**Model 4**	**Model 1**	**Model 3**	**Model 4**
Indonesian	**younger**	16	20	4	16	14	2
	older	10	4	9	12	16	10
German	**younger**	18	14	0	15	20	0
	older	14	6	2	18	12	6

(b)

		Carburetor1			Carburetor2		
		Model 1	**Model 3**	**Model 4**	**Model 1**	**Model 3**	**Model 4**
Indonesian	**younger**	12	12	6	10	6	10
	older	8	12	10	10	12	12
German	**younger**	14	16	8	12	10	16
	older	16	18	8	6	18	16

The deviation data is statistically analyzed using a chi-square test for both products. Table 3.31 shows the results of the chi-square test of the deviation data.

Table 3.31 The chi-square test results for deviations in the predicted LEGO brick (a) and carburetor part (b) position (Study 2).

(a)

	χ^2	df	p
Model	53.336	2	.000*
Assembly group	.731	3	.392
Culture	.015	1	.903
Age	.373	1	.541

*p<0.05

(b)

	χ^2	df	p
Model	24.364	2	.000*
Assembly group	.286	3	.593
Culture	1.136	1	.286
Age	.045	1	.831

*p<0.05

The chi-square results have not shown significant differences regarding assembly group, culture and age ($p > 0.05$). Thus, no further analysis is conducted for those variables. Significant differences are indicated in the model of robot behavior for both the product made from LEGO bricks and the carburetor ($p \leq 0.001$). Figure 3.56 depicts the predictive accuracy for the LEGO brick position, while Figure 3.57 shows the predictive accuracy for the carburetor part position depending on the model of robot behavior.

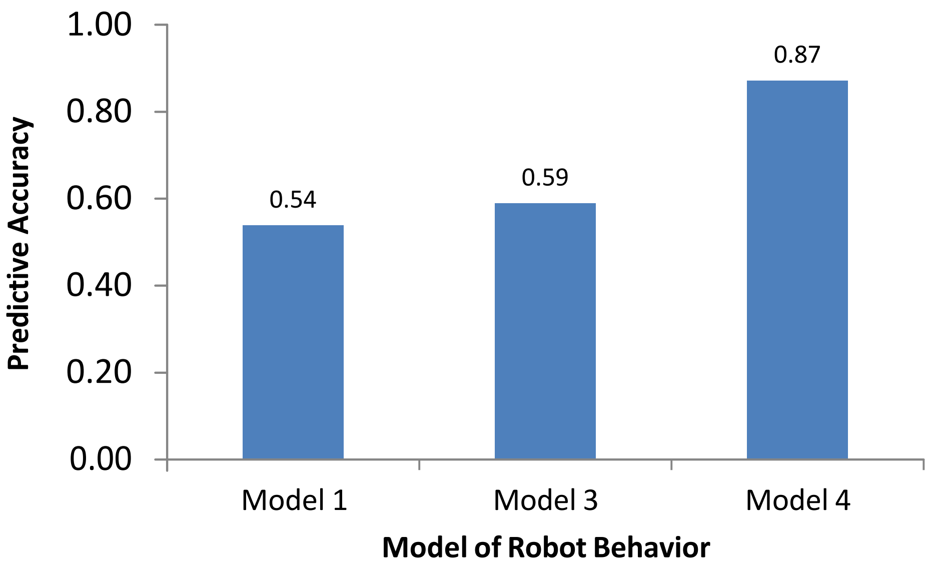


Figure 3.56 The predictive accuracy for the LEGO brick position for the three different models of robot behavior (Study 2).

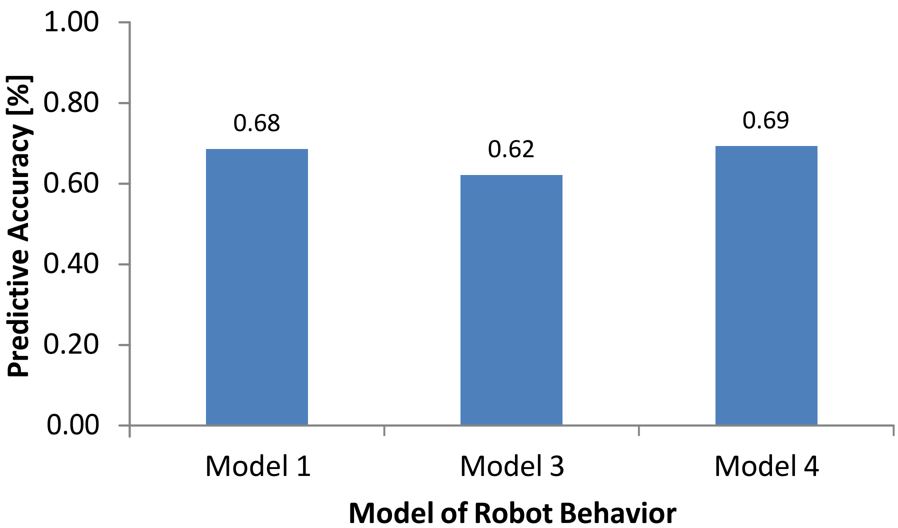
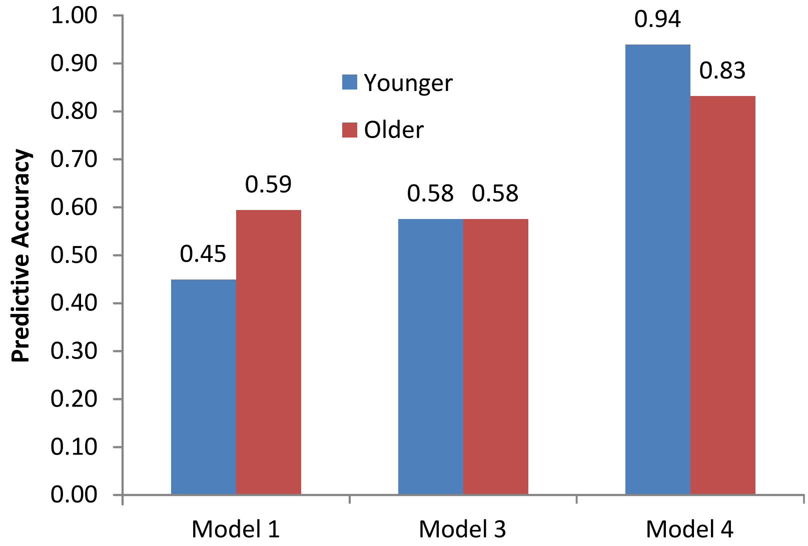


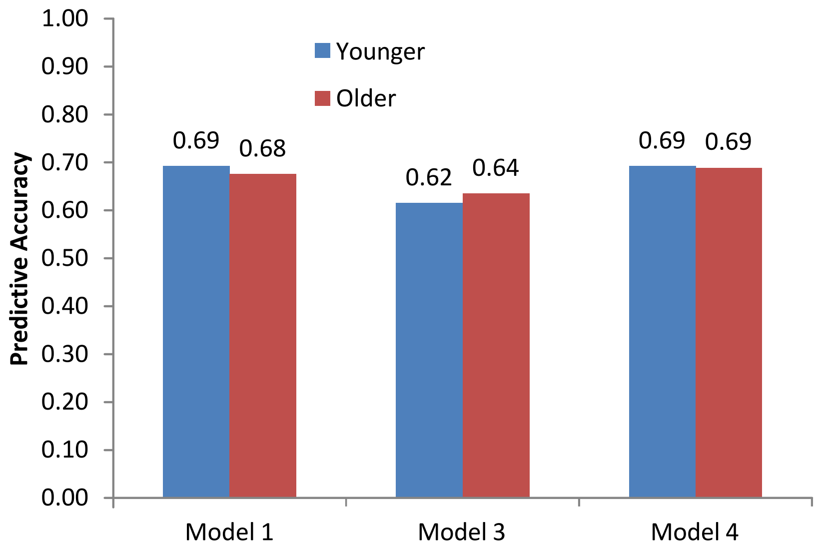
Figure 3.57 The predictive accuracy for the carburetor part position with the three different models of robot behavior (Study 2).

Figures 3.56 and 3.57 show that the highest predictive accuracy occurs (PA = 0.87 for LEGO products and PA = 0.69 for the carburetor, respectively) when Model 4 (the most human-oriented model) is used to control robot behavior.

Age and culture lead to insignificant differences in the deviation analyses. However, with regard to the focus of research, Figures 3.58 and 3.59 describe predictive accuracy depending on the age and the culture variables for each model. For instance, the predictive accuracy of the younger group is 0.62 with the LEGO and 0.53 with the carburetor. Within the older group, the predictive accuracy is 0.38 and 0.47 with the LEGO and carburetor products respectively. The predictive accuracy with the LEGO and the carburetor for the Indonesian participants is 0.46 and 0.43 respectively. Furthermore, slightly higher achievements are observed in the German group with around 0.54 and 0.57 for the product made from LEGO bricks and the carburetor products, respectively.

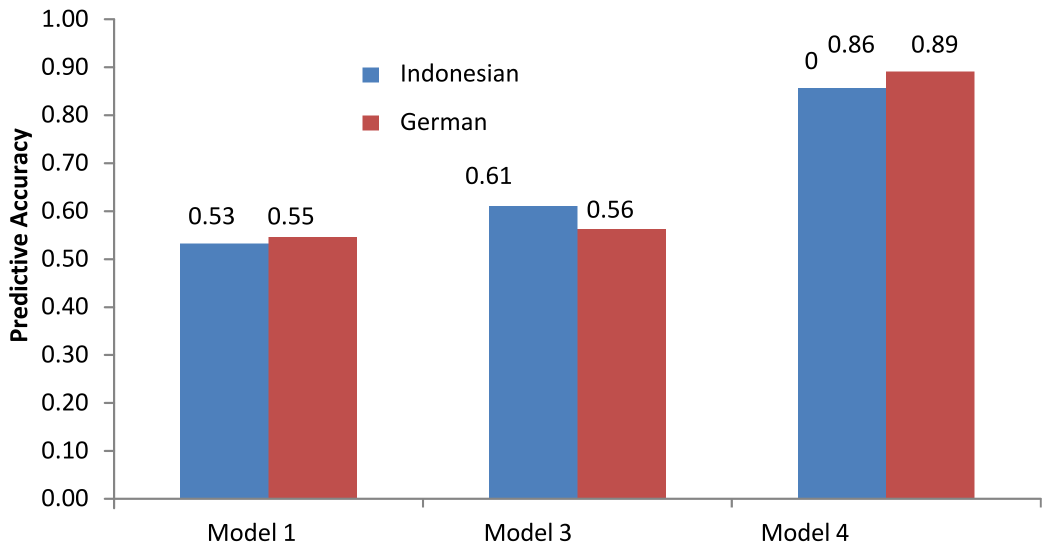


(a)

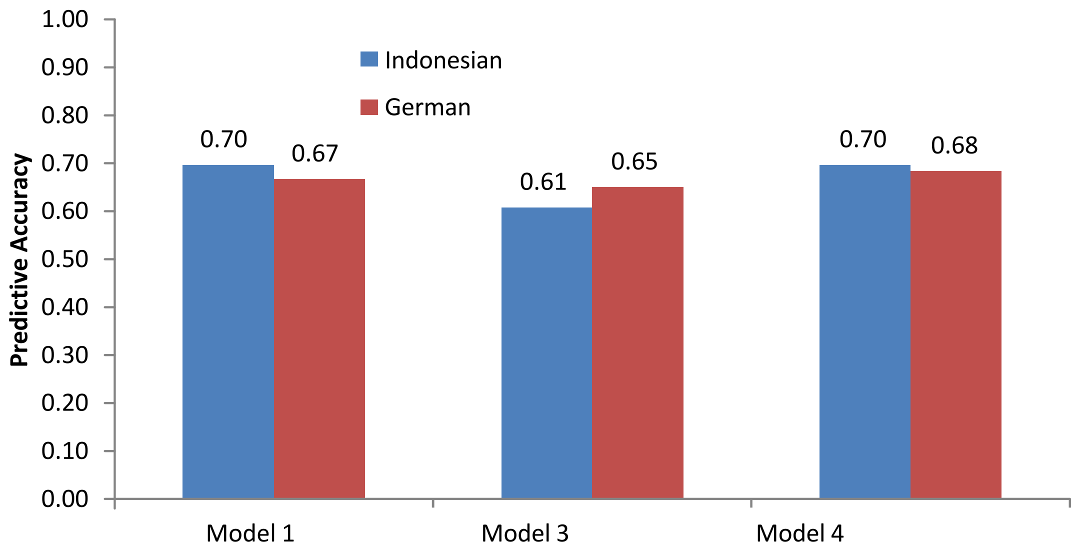


(b)

Figure 3.58 The predictive accuracy of the two different age groups with the product made from LEGO bricks (a) and the carburetor (b) (Study 2).



(a)



(b)

Figure 3.59 The predictive accuracy regarding the two different cultures with the product made from LEGO bricks (a) and the carburetor (b) (Study 2).

Based on the results of Study 1 and Study 2, it can be concluded that Model 4 – as the most human-oriented model – leads to the highest performance of the human operator as indicated by the shortest prediction time, the most recognizable strategy related to the results of assembly strategy evaluation by the participants, and the highest predictive accuracy. Model 4 also results in the lowest task loads and the lowest dissatisfaction grades in Study 1. Furthermore, Model 4 leads to the shortest fixation times for each AOI in Study 2. Thus, Model 4 is significantly improving the conformity with user expectations and can, therefore, contribute to a more safe and efficient human-robot interaction in self-optimizing assembly cells.

3.2.3 Discussion

Transferability of the Model of Robot Behavior

The two steps of the model transfer have to be carried out by the participants with the carburetor product. There are some facts here that should be considered in data analysis.

The first step is adapting the production rule to the new product structure. This mental operation is successfully applied in the products made from LEGO bricks. However, it is rather confusing when assembling the carburetor part. The human assembly behavior is transferred into the assembly sequence design as following: the screw assembling is started on the top side and proceeds in a clockwise direction. On the other hand, this assembly sequence is not compatible with machining procedure. Machining procedure sets the second screw diagonally from the first screw, or opposite each other, to maintain the position of the reinforcement part that needs to be screwed and to improve the easiness of part balancing (Workshop manual, 1998). Occasionally the participants with machining experience consider this fact and anticipate the assembly strategy differently. The comparison between the predictive accuracy of the model using this machining procedure (a) and the clockwise direction model (b) is shown in Figure 3.60. Since the participants with a professional education in engineering dominate the sample (70% of total participants) and the predictive accuracy of Model 4 with machining procedure is higher than with clockwise direction rule, machining procedure is then used to build Model 4.

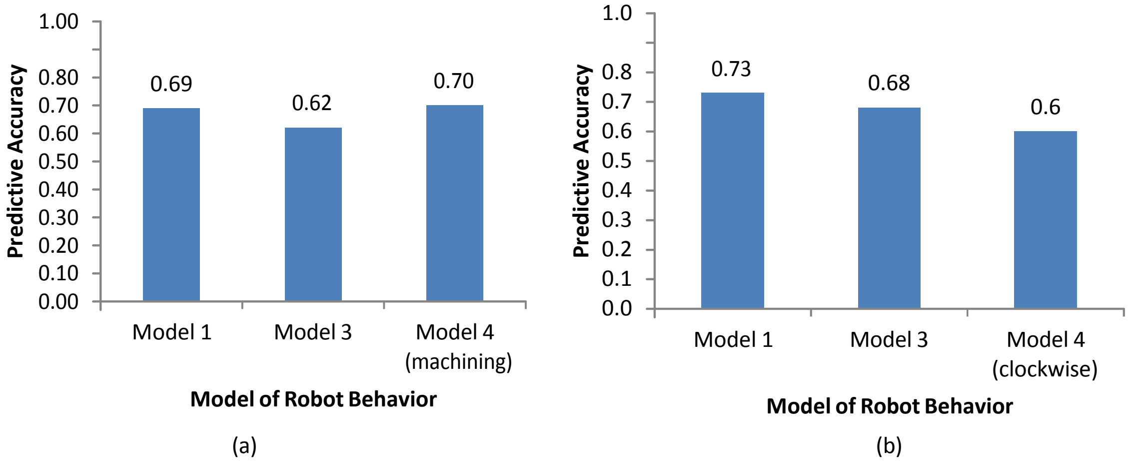


Figure 3.60 The predictive accuracy based on machining procedure (a) and a clockwise direction model (b)

Prediction time

The results of Study 2 reveal significant differences for the product made from LEGO bricks in the model of robot behavior and the age of the participants.

There are differences in the product made from LEGO bricks with respect to the model of robot behavior. Model 3 indicates a significant difference when compared to Model 4 ($p = 0.011$), while the comparisons between Model 1 and Model 3 ($p = 1.000$) and between Model 1 and Model 4 ($p = 0.067$) have not shown significant differences. Model 4 also leads to the shortest prediction time (mean = 4346.249 ms, SD = 2896.118 ms), while Model 3 leads to the longest prediction time (6057.451 ms, SD = 4854.008 ms). The average value of Model 1 is 5696.567 ms (SD = 4859.481 ms). This fact is explained by Hou and Wang (2010) regarding the necessity of human physical and mental compatibility during an assembly step. The neighborhood rule, which has a strong relationship with the layer rule in Model 3, causes confusion because of the incompatibility between the assembly sequence and prior experience. On the other hand, Model 1 is established without any rules in the assembly sequences. This means that participants recognize the assembly sequence as a stochastic mode of assembly and accomplish the assembly task faster than in Model 3. Model 4 – as the closest representation of human assembly strategy – leads to the most recognizable patterns by the participants and encourages ease in prediction task completion.

The younger group significantly differs from the older group with respect to the prediction time when performing correct predictions. The younger group (mean 4634.159 ms, SD = 3253.186 ms) shows a shorter prediction time than the older group (mean 6099.352 ms, SD = 5043.701 ms). This result is in line with the results of Pierson and Montoye (1958) where it is observed that a minimum reaction time and a maximum movement speed are achieved by the younger group (20 - 35 years old).

With the carburetor, significant differences in the prediction times are caused by the model of robot behavior. Similar to the prediction time results related to the product made from LEGO bricks, significant differences are found in comparisons between Model 3 and Model 4 ($p = 0.001$) and between Model 1 and Model 4 ($p = 0.032$). The comparison between Model 1 and Model 3 ($p = 0.097$) has not shown a significant difference. Model 4 leads to the shortest prediction time (mean = 10283.932 ms, SD = 5464.519 ms). In contrast to the process with the product made from LEGO bricks; with the carburetor, Model 1 results in the longest prediction times (mean = 12307.446 ms, SD = 7896.000 ms), while Model 3 occupies the middle position with the prediction times (mean = 11355.176 ms, SD = 8379.502 ms). It means that the participants encounter difficulties with distinguishing the rules in Model 1. Model 3 enable easier recognition than Model 1 due to the utilization of screws in the assembly sequence. The carburetor interim state is characterized by many possible positions of the predicted part. It utilizes at least three screws to express the layer rule in the model of robot behavior as defined in Section 3.2.1. The order of assembly using screws leads to the greatest ease in layer rule prediction with both Model 3 and Model 4.

The age of participants does not significantly influence prediction times with the carburetor. The descriptive statistic shows that shorter prediction times are found in the younger group than in the older group as described in Figure 3.31.

Cultural background has no significant effect on prediction times either for the product made from LEGO bricks or the carburetor. The descriptive statistical analysis shows that the German participants achieve faster prediction times than the Indonesian participants as shown in Figures 3.32 and 3.33.

It can be concluded that Model 4 leads to the best performance of the participants in terms of the shortest prediction times in Study 2, for both the product made from LEGO bricks and the carburetor. The human-oriented design is easily recognized by participants and the effects of the rules are quickly and accurately predicted.

Subjective Evaluation

- Task load

The first evaluation of the subjective evaluations made by participants in Study 2 is the task load. In the same way as in Study 1, the task load is assessed for each task. The task load data is structured chronologically and analyzed based on the independent variables.

The ANOVA results show a significant difference in the chronological development of the task load with the product made from LEGO bricks. The perceived task loads in Study 2 illustrate the tendency of task load increase with an increasing number of tasks as depicted in Figure 3.34 (a). It shows that the number of tasks contributes to the increase of the task load. With the carburetor, the chronological task load data based on the ANOVA result does not show significant differences as shown in Figure 3.34 (b). It means that the number of tasks does not affect the task load, even with the existence of the tendency towards task load increase between the first and the last tasks.

According to the independent variables, the ANOVA for the product made from LEGO bricks reveals significant differences in task load with regards to age and culture, as well as in the interaction between age and culture. Thus, an advance analysis on the interaction between age and culture is carried out.

The models of robot behavior and task load evaluation have not shown significant differences with the carburetor. With the product made from LEGO bricks, the ANOVA indicates a significant difference with the models of robot behavior. However, a significant interaction between age and culture also occurred. Thus, the basic descriptive statistical analyses are calculated to show the different performance of the models for both products as shown in Figure 3.35. Both the product made from LEGO bricks and the carburetor lead to the lowest task load perceived by participants using Model 4.

As shown in Table 3.21, significant differences in perceived task load with the product made from LEGO bricks are found in both younger and older Indonesian participants ($p = 0.001$). As reported by Sjahrir et al. (2001), the cognitive function of Indonesian people decreases from the age of 40 years old. Based on Mini Mental State Examination (MMSE), the MMSE scores are related to age. The scores range from a median 27 for those < 20 years of age, 28 for those 20 to 39 years of age, 26 for those 40 to 49 of years age, 27 for those 50 to 59 years of age, and 21 for those >60 years of age. Setiati et al. (2011) use the Abbreviated Mental Test (AMT) to investigate the cognitive status of Indonesian people. The results show significant differences in cognitive status between older and younger people. About 54% of cognitive impairment is found in the older group with an AMT score of 5.9. This result indicates that a poorer quality of life affects the physical and cognitive ability of the Indonesian elderly.

The German participants have not shown significant difference regarding age and task load ($p = 0.548$). This result is confirmed by Sproten et al. (2010). His study about cognitive processing in the decision making of German participants shows that a large part of the older adults' brains are still high functioning (with an active intellectual lifestyle). Moreover, even if their cognitive abilities decline, it generally happens at a much slower rate.

In the context of the significant differences in the perceived task loads between the German and Indonesian participants, the difference between Indonesian and German participants is related to lifestyle and cognitive activity. The German participants are more likely to be cognitively and intellectually active, while the Indonesian participants tend to have a poorer quality of life. Therefore, the cognitive status of German participants is higher than the Indonesian participants.

In the case of the carburetor, culture and age influence the task load independently. The Indonesian participants (mean = 2.7, SD = 2.5) sustain a higher grade of task load than the German participants (mean = 1.4, SD = 1.9). The mean value of the younger group's task load grade is 1.8 (SD = 2.1) and the task load grade of the older group is 2.3 (SD = 2.1). The explanation of these results is still related to the different conditions of the cognitive status of each participant group (Sjahrir et al., 2001; Sproten et al., 2010; Setiati et al., 2011).

- Dissatisfaction Grade

According to the chronologically structured data, the dissatisfaction grades recorded for Task 1 and those recorded for the other tasks in Study 2 are significantly different with regard to the product made from LEGO bricks. A tendency of increasing dissatisfaction is found based on the comparison between the dissatisfaction grade of the first task and the last task. For the carburetor, no significant difference is found. There is also no visible pattern or tendency that the dissatisfaction grade would increase, especially in the carburetor.

According to the independent variables, the ANOVA for the product made from LEGO bricks indicated significant differences in dissatisfaction grades regarding culture, age and the interaction between the culture and age. Thus, a post hoc comparison for the culture and age interaction is conducted.

The ANOVA have not shown any significant differences regarding the model of robot behavior and the carburetor with regard to dissatisfaction grades. The model of robot behavior with the product made from LEGO bricks shows a significant difference in dissatisfaction grades. However, an interaction between age and the culture is also indicated. The descriptive statistic is then performed to show the differences in dissatisfaction grades depending on the robot behavior model (see Figure 3.40). Model 4 reveals the lowest dissatisfaction grade both for the product made from LEGO bricks and the carburetor.

The pairwise comparisons of the culture and age interaction for the product made from LEGO bricks point out a significant difference in the dissatisfaction grades from the Indonesian participants ($p = 0.003$). The age group of the German participants does not show significant differences ($p = 0.913$). This means that the cognitive function of the older Indonesian participants decreases more than the older German participants. Cognitive function related to the speed of cognitive process, capacity and robustness of the memory appear to decrease progressively with age. The study result of Sjahrir et al. (2001) show that the cognitive status of Indonesian people related to the memory recall decreases with age. The ageing process (especially below 60 years of age) does not affect significantly the cognitive status of German people since the German have tendency to have a more active intellegently than Indonesian (Sproten et al., 2010). German participants tend to develop a strategy in order to understand the assembly sequences pattern based on their prior experience, which therefore leads to a lower dissatisfaction grade.

With the carburetor, the Indonesian participants reach a higher value of dissatisfaction grade (mean 4.7, SD = 2.5) than the German participants (mean = 2.9, SD = 3.2). This means that the Indonesian participants experience more difficulties in defining the strategy of the robot behavior model than the German participants. With the Indonesian participants, the age variable of the younger group also differs from the older group. The younger group achieves a lower value of dissatisfaction grade (mean = 3.5, SD = 2.9) than the older group (mean = 4.1, SD = 3.0). The younger group is more comfortable in defining the strategy of the robot behavior model than the older group. These facts are related to the explanation of the physical and cognitive condition of each age group (Sjahrir et al., 2001; Sproten et al., 2010; Setiati et al., 2011).

- Assembly Strategy Evaluation

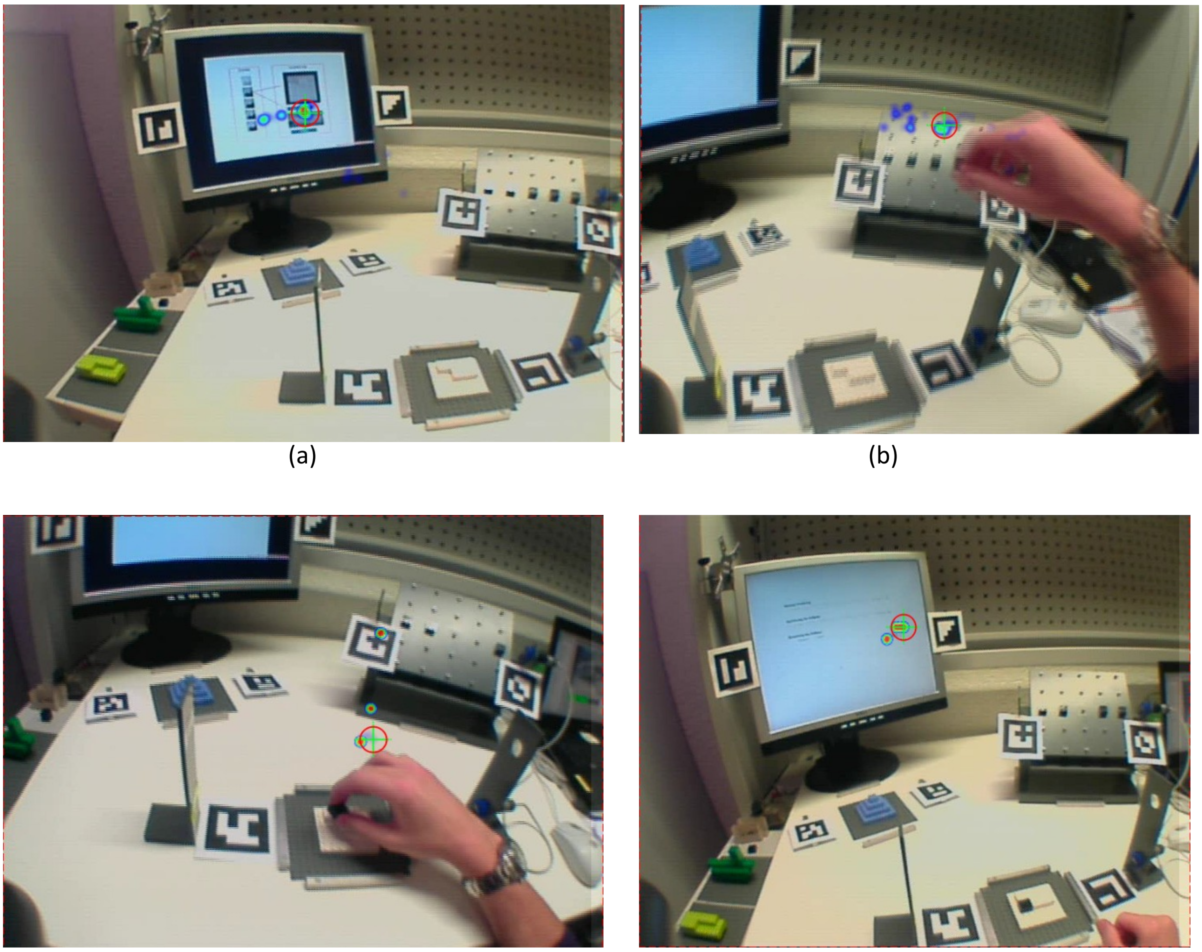
With respect to Cochran's Q test, there are significant differences between the models of robot behavior for both the product made from LEGO bricks and the carburetor. The pairwise comparison denotes differences between Model 1 and Model 3, as well as between Model 1 and Model 4 respectively. It is shown in Table 3.24 and Figure 3.44 that Model 4 – as the most human-oriented model – is recognized as utilizing a strategic approach in assembly sequences (82% for the LEGO and 73% for the carburetor). On the other hand, Model 1 – as the reference model with the lowest number of human-oriented production rules adoption – is recognized by participants as having a stochastic approach (71% for the product made from LEGO bricks) in assembly sequences. With the carburetor, Model 1 is quite often considered to follow a certain assembly strategy (56%) due to the lack of comprehension of neighbor relationship and the aforementioned background.

The age and culture have not shown significant differences in the strategy recognition based on the result of the Cochran's test. A descriptive statistic is graphically described in Figures 3.45 and 3.46. Figure 3.45 shows that Model 4 – as the most human-oriented model – is recognized as using an approach of human assembly behavior by both for the younger (the product made from LEGO bricks and the carburetor are around 87% and 78%, respectively) and the older group (the product made from LEGO bricks and the carburetor are around 77% and 68%, respectively). Figure 3.46 describes that both of the Indonesian (77% for the product made from LEGO bricks and 65% for the carburetor) and the German participants (87% for the product made from LEGO bricks and 82% for the carburetor) comprehend Model 4 as using a strategic model of the assembly.

These results are in line with the prior expectation that Model 4 is considered and not rejected by participants as using a premeditated strategy. The evaluation results show that a higher conformity of user expectation is reached if Model 4 is taken into account to control the assembly robot.

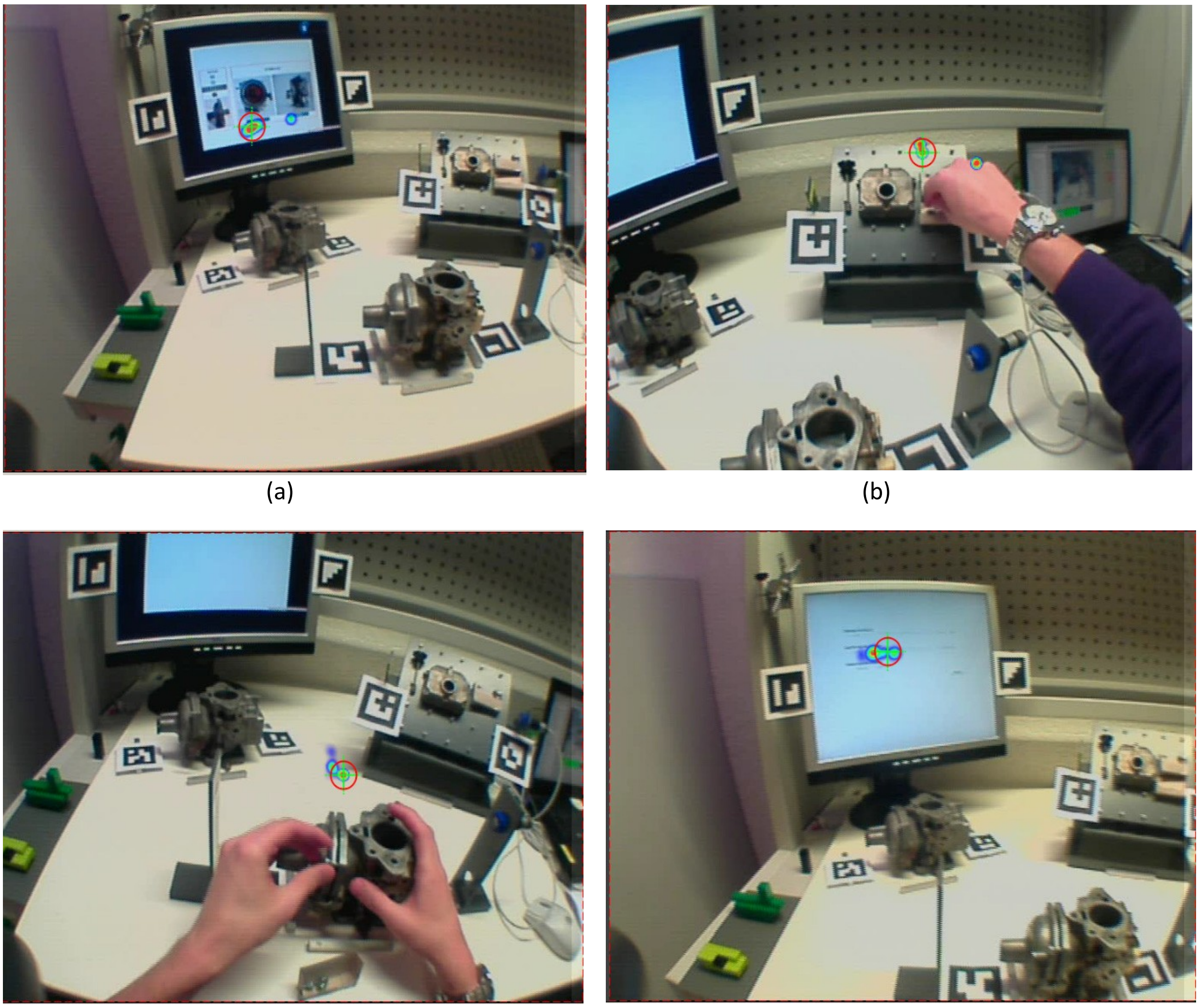
Area of Interest (AOI)

In addition to the previous analysis, the eye-tracking system was used to examine the area of interest (AOI) during the execution of assembly tasks. As shown in Figure 3.27, there are four AOI in Study 2. The data of fixation duration is obtained from the recorded video files based on the eye pupil movement and heat map analysis using D-Lab Analysis software. Figures 3.61 and 3.62 show a heat map analysis of the assembly of the product made from LEGO bricks and the carburetor respectively.



(a) (b) (c) (d)

Figure 3.61 Heat map analysis of AOI 1(a), AOI 2(b), AOI 3(c) and AOI 1 in subjective evaluation (d) of the product made from LEGO bricks.



(a) (b)

(c) (d)

Figure 3.62 Heat map analysis of AOI 1(a), AOI 2(b), AOI 3(c) and AOI 1 in a subjective evaluation (d) of the carburetor.

According to Figures 3.61 and 3.62, the fixation duration for each AOI is computed. The heat map analysis of AOI 4 only contained few data due to the low attention and interest of the participants in the completed assembly group shown in AOI 4. This fact is discussed further in the gaze behavior section.

Occasionally, a lack of conformity between the heat map (and the eye pupil movement) and participant's activity is detected as shown in Figure 3.63. For example, the participant is working in the assembly work area. However, the heat map analysis indicates that the participants pay attention to AOI 4. This means that while participant's arm is moving in the assembly area, their fixation focuses on the example of the completed object in AOI 4. As a result, there is divided attention in this case (Spelke et al., 1976). In this situation, AOI 4 is selected as the point of interest, and the duration of this activity is recorded as the AOI 4 duration.

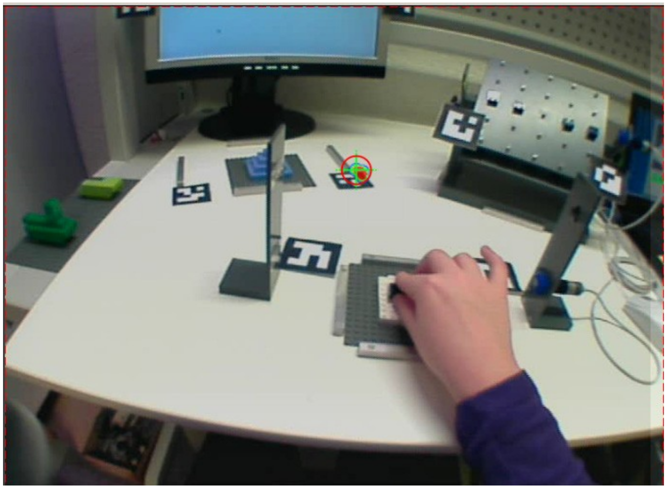


Figure 3.63 The divided attention in AOI.

According to the ANOVA results based on the independent variables with the product made from LEGO bricks, there are significant differences in fixation duration for the interaction between the model of robot behavior and the assembly group, as well as between the assembly group and the AOI. Further analyses of the interaction are taken into account.

The post hoc analysis of fixation duration between the models and the assembly groups shows significant differences in the pyramid interim state between Model 1 and Model 3, as well as between Model 3 and Model 4. The fixation duration of the participants during the assembly simulation with Model 4 indicates the shortest duration (mean 8424.788 ms, SD = 11332.006 ms for the pyramid and mean = 8012.500, SD = 10739.965 ms for the ship). Based on this indication, the built in production rules are accepted by the participant as the most recognizable and understandable strategy in the assembly task. This means that Model 4 encourages a shorter duration of fixation by participants than with other models. As shown in Figure 3.47, Model 1 leads to shorter fixation duration periods (mean = 8970.551, SD = 11327.559 ms for the pyramid and mean = 8465.244 ms, SD = 10965.911 ms for the ship) than Model 3 (mean = 11498.242 ms, SD =13.698.841 ms for the pyramid and mean = 8922.613, SD = 11071.153 ms for the ship). These results are in line with the results of Study 1 and the prediction time result regarding cognitive compatibility during the assembly task. Hou and Wang (2010) state that it is necessary to consider the compatibility of the human physical and mental state during the assembly step. The strong relationship between the neighborhood and layer rules in Model 3 affect the mental model and the interest area of the participants due to the incompatibility of the assembly sequence and prior experience of participants. On the other hand, Model 1 is established without any human-oriented rules in its assembly sequences. The participants recognize the assembly sequence in Model 1 as a stochastic mode, and by doing so they feel more confident in accomplishing the assembly task. As a result, Model 1 leads to shorter fixation duration periods than Model 3.

The second further analysis with the product made from LEGO bricks is conducted for the interaction between the assembly group and the AOI. Significant differences in fixation duration between the assembly group and the AOI are revealed. The pyramid interim state leads to longer fixation duration than the ship interim state. For example, the fixation duration for the pyramid in AOI 1 is 29054.017 ms (SD = 5447.105 ms), while the fixation duration for the ship in AOI 1 is 26414.863 ms (SD = 2832.085 ms). This means the pyramid requires more attention in all AOI than the ship.

The ANOVA result for the carburetor shows a significant difference in fixation duration between the model of robot behavior and the AOI. As shown in Figure 3.48, Model 4 also leads to the shortest fixation duration in all AOI, while Model 1 reveals the longest fixation duration in AOI 1, AOI 2 and AOI 3.

This finding confirms the prior hypothesis that cognitive control as represented by Model 4 can be adopted to a technical system as indicated by the shorter attention duration required during assembly execution.

The variable of culture has not shown significant differences in fixation duration, both for the product made from LEGO bricks ($p = 0.922$) and the carburetor ($p = 0.955$). The descriptive statistical analysis shows the difference in fixation duration between the Indonesian and the German participants. Figure 3.49 shows that the German participants achieve shorter fixation duration than the Indonesian participants for both the product made from LEGO and the carburetor.

Predictive Accuracy

The predictive accuracy represents the relative frequency of the correct part position. The predictive accuracy depending on the model of robot behavior shows that Model 4 leads to the highest predictive accuracy, both for the product made from LEGO bricks and the carburetor. Similarly, the predictive accuracy found with Model 4 based on the categorization of age and culture show the highest predictive accuracy. These results mean that the cognitive compatibility of Model 4 leads to the highest performance in the prediction task.

Gaze Behavior

In addition to the fixation duration, the gaze behavior data is also analyzed with respect to the working area in the recorded video files. The participants followed a similar pattern regarding gaze behavior during Study 2, as shown in Figure 3.64.

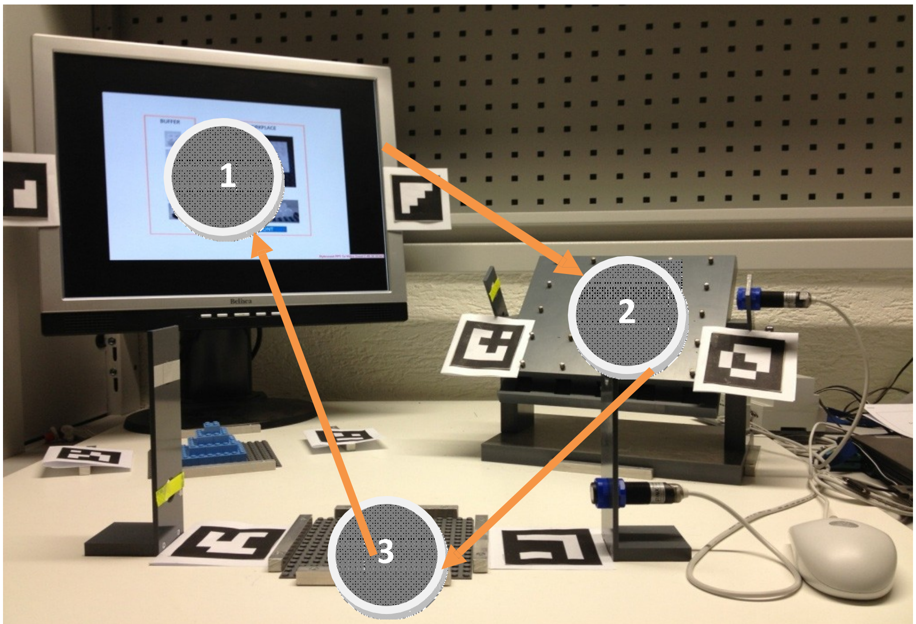


Figure 3.64 General gaze behavior of participants in Study 2.

Participants generally start to focus on AOI 1 that visualizes the assembly sequences. After the simulation is finished, participants switch to the AOI into the part area (AOI 2). Attention is then shifted to AOI 3, which is the assembly work area. Afterwards, the participants return to AOI 1 to complete the subjective evaluation of the task. There is only a low attention focus from participants on AOI 4. However, during Study 2, there are also different gaze behaviors, as shown in Table 3.32.

Table 3.32 Specific style of the gaze behavior based on AOI.

Nr.	Gaze behavior based on AOI	Number of participants			
		German		Indonesian	
		LEGO	Carbu.	LEGO	Carbu.
1.	1 → 3 → 1 → 2 → 3 → 1	1	7	3	6
2.	1 → 4 → 1 → 2 → 3 → 1	2	1	2	4
3.	1 → 3 → 4 → 2 → 3 → 1	0	1	0	0
4.	1 → 2 → 4 → 3 → 1	2	2	1	1
5.	1 → 2 → 3 → 2 → 3 → 1	0	4	1	6

According to Table 3.32, the carburetor assembly requires more attention in AOI 3 than the product made from LEGO bricks. About 50% of the participants experience the necessity to check the interim state of the work object during the simulation of the assembly sequence on the screen. The frequency of attention shifting from AOI 1 to AOI 3 during the visualization varies between one and up to four times for Indonesian participants, and one or two times for the German participants. Despite almost equivalent number of participants with the general style of gaze behavior, the Indonesian participants tend to ensure the equivalency of the actual work object with the simulated object on the screen more than German participants. This fact is concomitant with Nisbett and Norenzayan (2002) regarding the cognitive processes of Westerners and Easterners. In this study, the German participants pay more attention to the visualized object as the primary intention during the assembly sequence visualization. The Indonesian participants tend to pay attention more to the relationship between the actual work object and the visualized object on the screen.

The difference of gaze behavior type, as shown in fifth gaze behavior in Table 3.32, is indicated when the presentation of assembly sequence is finished, and the participants are expected to determine the next assembly part. The Indonesian participants have less confidence in making decisions about the selection of the next part than the German participants. They require more certainty on the selected fitting part for the actual object work than the German participants. Thus, the Indonesian participants more often shift their attention to AOI 3 before determining the selected part than the German participants. The discussion of control and confidence levels of the participants during decision making is also in accordance with the findings of Nisbett and Norenzayan (2002).

3.3 General Discussion

3.3.1 Influence of Age and Culture

The main objective of the age- and culture-differentiation in this study is to examine whether the cognitive ergonomic approach to the user-centered design of the CCU in the assembly work system is effective for workers from various cultural backgrounds. Because manufacturing becomes more competitive and globalized due to increasing product values, it is critical to focus on work system design in the long term, especially based on the cultural backgrounds that are related to different regions in the world and the age group of the worker in the specific region.

The pyramid shape of the world's population shows an increase in the average worker age within a very close time frame. This suggests the necessity of an age-differentiated work system design. The average age of workers increases precipitously with the decreasing size of the working population (Nägele, 2007; Toosi, 2007; Göbel and Zwick, 2011). To preserve the level and stability of work system performance, the age of the working population should be considered. The design of a self-optimizing work system is expected to be able to accommodate differences between age groups. Study 2 points out the influence of the different age groups on the prediction time, task load and dissatisfaction grade. However, these effects are only significant if age interacts with assembly group and culture. The perceived task loads and participant dissatisfaction grades also show significant differences given the interaction between age and culture. In this case, only the age groups of the Indonesian participants lead to a significant difference in the value of the task load and the dissatisfaction grade. The interaction between age and culture in the subjective evaluation is explained in Section 3.2.3. To conclude, the Indonesian participants have a tendency to work with lower performance due to ageing, while the German participants have not shown a tendency of decreasing performance caused by ageing in this study. This phenomenon is related to the different cognitive status of the human worker based on their cultural background and lifestyle (Sjahrir et al., 2001; Sproten et al., 2010; Setiati et al., 2011).

Because automation is an important current trend and one of the alternative solutions for staying competitive both in the high-wage and low-wage countries, the work system design should be carefully planned regarding long-term utilization of the equipment and the high costs of system maintenance. As the automation of work systems is dominated by high-wage countries such as Germany, a cultural study of robot-supported assembly work is an essential factor in work system design. This would mean that the operator in an automated assembly system could be either an European worker in the "Western" design of the working system environment, or an "Eastern" worker with a "Western" design and "Eastern" working environment. Furthermore, the conformity between the "Western" work system design and the international or local design becomes an important criterion to achieve the automation objective of conserving and increasing the worker performance (Klocke, 2009). Figure 3.65 describes how the automation system design is applied in high-wage and low-wage countries.

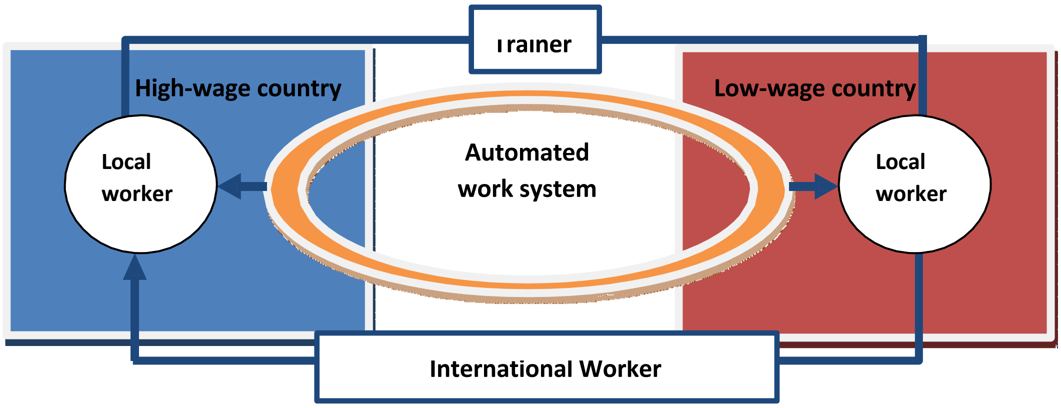


Figure 3.65 Design of automated work system applied in high- and low-wage countries.

According to the results of Study 1, culture as a main independent variable has not lead to any significant differences in the participant's performance regarding the prediction time, task load or dissatisfaction grade. However, the result of Study 2 indicates a significant difference in prediction time with regard to the age variable. Furthermore, cultural background also affects the task load and dissatisfaction grade due to its interaction with the age. In addition, the cultural background also influences gaze behavior, as discussed in Section 3.2.3.

3.3.2 The Role of the Cognitive Control Unit in the User-Centered Design of Self-Optimizing Assembly Systems

A cognitive control unit is established as an innovative programmable control system in the robotized production system that adopts human cognition. A CCU is expected to be able to simulate rule-based human behavior in a technical system. With regard to the human operator and CCU interaction in the assembly work system, improving system transparency for the human operator is a pivotal point. Conformity between an operator's expectations and the self-optimizing assembly processes is expected to increase with the implementation of a CCU with a user-centered design.

As the designer of the knowledge base at the CCU, Mayer et al. (2011) develops nine models of assembly strategy based on three production rules of human assembly behavior in conjunction with the MTM-1 system. By focusing on six models, Mayer et al. (2011) investigate the predictability of robot behavior in the assembly processes. This study adopts four of these models of robot behavior for Study 1 and three models for Study 2 as one of the independent variables. The model of robot behavior influences the worker's performance regarding the objective and subjective evaluation data in Study 1. Furthermore, it results in significant differences in prediction time, assembly strategy evaluation and fixation duration based on the interaction between the assembly group and the AOI. It can be concluded that to certain extent, the human cognitive process can be simulated and implemented in a CCU. The CCU also supports and improves conformity with operator expectations during the supervision of the assembly processes.

In conclusion, human assembly strategies are fundamental in user-centered CCU design. As the human operators have the most important role in a self-optimizing assembly system, they have to interact effectively, efficiently and safely with the robot and to solve the problems that were not anticipated by the work system designers. The results of the empirical studies show that the mode with the most human-oriented behavior – Model 4 – leads to the highest performance from the human operator. This means participants consider Model 4 to have the most legible robot behavior. A higher legibility of the robot behavior leads to a higher perceived safety of the human operator in a virtual human-robot interaction. As stated by Lichtenhaeler et al. (2012), “the robot behavior is legible if a human can infer the next actions, goals and intentions of the robot with high accuracy and confidence”. Thus, the shortest prediction time and the highest predictive accuracy involved with Model 4 show that the adapted human assembly strategies in robot behavior leads to higher predictability of robot behavior. Furthermore, it improves the perceived safety of human operator when working with the robot.

The user-centered design of CCU aims at the conformity between human procedural knowledge and robotized work processes, as well as in achieving the generality of self-optimizing assembly system design. Tables 3.33 and 3.34 summarize the effects of the independent variables on human performance and behavior as guidance to the user-centered design of CCU in self-optimizing assembly systems.

The main point of the guideline based on Table 3.33 (for the product made from LEGO bricks) and Table 3.34 (for the carburetor) is that the model of robot behavior, assembly group, age and culture affect the human performance either independently or in interaction with the other variables. These variables should be carefully considered during the work system design and the human operator training phase.

Table 3.33 Summary of significant effects of the independent variables on human performance and behavior in the simulated robot-supported assembly task (using LEGO products, α = 0.05).

		Influence on human performance and behavior					
		Prediction Time	**Task Load**	**Dissatisfaction Grade**	**Assembly Strategy Evaluation**	**Fixation Duration**	**Gaze Behavior**
Study 1							
1	Culture differentiation	No	No	No	-	Not investigated	Not investigated
2	Length of prior assembly cells	No	No	No	-	Not investigated	Not investigated
3	Assembly groups	Yes	No	No	-	Not investigated	Not investigated
4	Models of robot behavior	Yes	Yes	Yes	Yes	Not investigated	Not investigated
Study 2							
1	Culture differentiation	No	Yes, interaction with age	Yes, interaction with age	-	No	Yes
2	Age-differentiation	Yes	Yes, interaction with culture	Yes, interaction with culture	-	No	Not investigated
3	Assembly groups	No	No	No	-	Yes, - interaction with model - interaction with AOI	Not investigated
4	Models of robot behavior	Yes	No	No	Yes	Yes, - interaction with assembly group	Not investigated
5	Area of interest (AOI)	-	-	-	-	Yes, interaction with assembly group	Not investigated

Table 3.34 Summary of significant effects of the independent variables on human performance and behavior in the simulated robot-supported assembly task (using carburetor, α = 0.05).

<table>
<tr><th colspan="2"></th><th colspan="6">Influence on human performance and behavior</th></tr>
<tr><th colspan="2"></th><th>Prediction Time</th><th>Task Load</th><th>Dissatisfaction Grade</th><th>Assembly Strategy Evaluation</th><th>Fixation Duration</th><th>Gaze Behavior</th></tr>
<tr><td colspan="8">Study 2</td></tr>
<tr><td>1</td><td>Culture differentiation</td><td>No</td><td>Yes</td><td>Yes</td><td>-</td><td>No</td><td>Yes</td></tr>
<tr><td>2</td><td>Age-differentiation</td><td>No</td><td>Yes</td><td>Yes</td><td>-</td><td>No</td><td rowspan="4">Not investigated</td></tr>
<tr><td>3</td><td>Assembly groups</td><td>No</td><td>No</td><td>No</td><td>-</td><td>No</td></tr>
<tr><td>4</td><td>Models of robot behavior</td><td>Yes</td><td>No</td><td>No</td><td>Yes</td><td>Yes, interaction with AOI</td></tr>
<tr><td>5</td><td>Area of interest (AOI)</td><td>-</td><td>-</td><td>-</td><td>-</td><td>Yes, interaction with model</td></tr>
</table>

4. CONCLUSIONS AND FUTURE WORK

4.1 Conclusions

Based on the consolidated findings that were presented and discussed in the previous section, the research questions that were formulated in the introduction are reflected in the following with the attempt to find precise answers.

1. *Based on an architecture of human cognition, how can a robot simulate human rule-based behavior so that it can adapt to the changing conditions of the assembly environment and also simulate human assembly heuristics to improve conformity to operator's expectations?*

According to the established models of human cognition, a working person naturally applies previously accumulated declarative and procedural knowledge to the next task. If the next step within that task is incompatible with the prior knowledge, the person requires a longer time to understand the current step and to anticipate the next action. Furthermore, the learning process during the assembly process becomes longer and more strenuous due to the difference between the rule-based prediction on one hand and the actual system behavior on the other hand.

The process of designing a self-optimizing assembly cell for cognitive compatibility requires a cognitive simulation model that can adapt to the changes of the production environment. The studies, which focus on the adaptation of robot behavior to the human assembly behavior in the assembly work system, descriptively and statistically confirm this statement.

The statistical analysis reveals that the model of robot behavior mainly influences the worker's performance, reliability and subjective mental workload. There are four models of robot behavior investigated in Study 1, whilst three models of robot behavior are investigated in study 2. The most important finding is that the most human-oriented assembly behavior patterns as represented in Model 4, lead to the participant's highest performance in term of the shortest prediction time, the evaluation of robot behavior as strategically acting, and the shortest fixation duration. However, the models of robot behavior significantly interact with the assembly group (in LEGO product) and the AOI (in carburetor product). In the task load and dissatisfaction grade evaluation of Study 2, the models of robot behavior do not lead to any significant differences in the dependent variables. However, based on the inferential statistical evaluation, Model 4, which features the most human-oriented model in terms of the highest number of human-oriented production rules, leads to the lowest task load and the lowest dissatisfaction grade of the participants during the simulated robotized assembly task. Model 4 also leads to the highest performance of the participants in terms of shorter prediction times, lower task load and higher predictive accuracy.

Therefore, it can be concluded that human assembly behavior can be encoded by additional production rules in the knowledge base and effectively executed as a cognitive ergonomic assembly strategy in the CCU. It is also shown that this cognitive ergonomic assembly strategy supports the conformity of operator expectation during the supervision of the robotized assembly processes.

2. *How can human assembly strategies be identified and transferred from a model product into a manufactured product?*

Human assembly strategies are identified by encoding the human-rule based behavior during assembly task into a number of production rules in a knowledge base. The strategies include the vicinity of the neighboring parts and the build-up of layer rules. In this study, the highest number of production rules represents the most human-oriented model design.

To transfer the concept of human-oriented design, the first step is to adapt the production rules to the new product structure. This transfer becomes difficult for the assembly sequence of a screw part because it affects established machining procedures. If participants possess a certain level of machining knowledge, they sometimes have a different view on the assembly rules and consider the standard assembly procedures as more effective.

The second step is to develop an adequate set of layer rules for the carburetor part that can be executed effectively in the carburetor assembly. The human-oriented production rules in Model 4 expect the next position of the screw to be on the bottom right side. However, similar to the first phase of the technical transfer, the established machining procedure sets the screw diagonally instead of following the clockwise order. Based on this finding, the assembly sequences in Model 4 are adjusted to follow preferred machining procedures. The analysis of the expected part in Model 4 is conducted based on these rules, as well.

The transfer of the model of robot behavior was successfully conducted for the carburetor part. The results of Study 2 confirm the machining process-oriented usage of the screws to anticipate the assembly sequence. This leads to higher predictability of the model of robot behavior, especially for Model 3.

3. *How do age and cultural background influence human performance, reliability and subjective mental workload when interacting with the CCU of a self-optimizing assembly cell?*

In the two studies conducted in this thesis, significant differences between the younger and older participants regarding both the perceived task load and the dissatisfaction grade were observed. In addition, it was statistically proven that cultural background interacts with age. The analysis also reveals differences in task load and dissatisfaction grades between German and Indonesian participants when regarding both the product made from LEGO bricks and the carburetor assembly. The ANOVA results show that the German participants did not perform differently to any significant degree with regards to age, whilst the Indonesian participants do show a significant difference between age groups. The descriptive analysis shows that the perceived task load of the Indonesian participants is on average higher than the German participants. The difference between Indonesian and German participants is related to the lifestyle and cognitive activity. The German participants are cognitively and intellectually active, while the Indonesian participants tend to be more passive and to have a lower quality of life. Therefore, the cognitive functional state of German participants seems to be better than that of the Indonesian participants (Sjahrir et al., 2001; Sproten et al., 2010; Setiati et al., 2011).

Based on the result of these empirical studies, it can be concluded that different kinds of assembly groups significantly influence prediction time and the fixation duration during the assembly task. A complicated assembly group design leads to a longer prediction time and a longer fixation duration than a simple design. Similarly, the technical transfer from a product made from LEGO bricks into a carburetor also influences the prediction time and the fixation duration. Prediction time and fixation increased by approximately 100% when using the carburetor in comparison to the LEGO product with regard to the complexity of the product structure.

The two studies conducted in this thesis led to several important statistical results. Most prominently, Model 4, which is based on the most human-oriented production rules, leads to the shortest prediction times, the highest prediction accuracy, the lowest task loads, the lowest dissatisfaction and the highest perceived familiarity. These results can be reproduced for both for the simple LEGO product and the complex carburetor product.

In addition, a significant effect of cultural background is found. Firstly, Indonesian participants perceive a higher level of task load than the German participants. Secondly, the task load of the Indonesians correlates with age, in contrast to the Germans. Thirdly, the Indonesian participants exhibit a different gaze pattern, focusing more on the similarity of the actual work object with the simulated object on the screen, whereas the German participants pay more attention to the assembly sequence simulation. Finally, age effects are also confirmed, but interestingly, more for the Indonesian than for the German participants. In the following paragraphs, these results are described in detail.

Study 1

The results of Study 1 show that Model 4, which includes the most human-oriented production rules of the four models used in this thesis, is evaluated by the participants as an influential and strongly strategic model in the self-optimizing assembly system. The results are confirmed based on the analysis of the prediction times and subjective evaluations.

The analysis of the prediction times results in significant differences for the models of robot behavior and the assembly groups. The comparisons between Model 4 and the three less human-oriented models show significant differences. These results indicate that Model 4 stimulates understanding of the robot behavior and accelerates the learning process of the following action prediction. Model 4, which is the most human-oriented model, leads to the shortest prediction time, and is evaluated by the participants as acting strategically. It is compatible with the human tendency to predict the position of the next brick based on his/her experience with the neighborhood rule. Thus, the participants require less time to predict the next brick position due to the ease of assembly strategy analysis.

The task load appeared to increase slightly with the increasing number of processed tasks. The usage of Model 4 leads to the lowest task load. It can be concluded that the most human-oriented behavior leads to the least task load for the participants when predicting the brick position.

In addition, Model 4 leads to the lowest dissatisfaction grade. These facts demonstrate the cognitive compatibility of the identified patterns and their interpretation as an assembly strategy.

The simulated cognitive processes in Model 4 are reported as being easily interpreted by the participants and considered as having a familiar strategy in assembly sequences (81%), while Model 1, which is the least human-oriented model, is considered by the participants as an incomprehensible cognitive controller and considered acting randomly, without apparent sub-goals or purpose (64%). Model 4 also leads to the highest predictive accuracy (PA = 0.85).

Study 2

Study 2 led to results that are consistent with Study 1. The ANOVA of the prediction time in Study 2 highlights significant differences regarding the models of robot behavior and age. When assembling the LEGO product, regarding age, the younger group predicts significantly faster than the older group. In the case of the carburetor, significant differences of the prediction time are obtained for the models of robot behavior. The post hoc analysis with Bonferroni correction shows that the shortest prediction time is related to Model 4, which includes the most human-oriented production rules, both for the product made from LEGO bricks and the carburetor.

ANOVA results also show significant effects regarding the task load. If the execution time increases, the task load increases accordingly. According to the independent variables, the ANOVA for the LEGO product reveals significant differences of the task load with respect to main factors of cultural background and age, as well as the mutual interaction between these variables. In the comparison between the younger and older Indonesian participants, a significant difference of task load is found with the product made from LEGO bricks. This effect cannot be reproduced for the German participants. For the carburetor, it is found that both the culture and age independently influence the level of the task load. The Indonesian participants perceive a higher level of task load than the German participants. In addition, the task load for the group with the older participants is higher than of the group with the younger participants.

Furthermore, it was observed that the grade of dissatisfaction in Study 2 significantly increases over time with an increasing number of tasks undertaken. However, there is no visible pattern or observable tendency for the growing dissatisfaction, especially regarding the carburetor. According to the independent variables, the ANOVA results for the LEGO product indicate significant differences in dissatisfaction grades depending on culture and age, as well as the interaction between the culture and age. The post hoc comparison for the analysis of the interaction between culture and age show that a significant difference is only found for the comparison between the younger and the older groups of the Indonesian participants. For the carburetor, it becomes evident that both culture and age are independent variables that lead to significant differences in the dissatisfaction grade. Similarly, with the post hoc analysis for the task load, the dissatisfaction grade of the Indonesian participants is higher than that of the German participants. The older group also perceives a higher dissatisfaction grade than the younger group.

In the evaluation of assembly strategies, there are significant differences between the models of robot behavior with LEGO and carburetor products. With the LEGO product, Model 4, which includes the most human-oriented production rules of the three models used in this thesis, is evaluated to act strategically in the assembly sequence (82% for the product made from LEGO bricks and 73% for the carburetor). Model 1, which acts as the reference model and includes the least human-oriented production rules of the three models, is regarded by the participants as a randomly acting model (71% for the product made from LEGO bricks).

Regarding the carburetor, in contrast to the findings in the LEGO setting, the majority of the participants claim that Model 1 follows an assembly strategy (56%), which is due to over-interpretation of the simple motion cycle and the aforementioned machinery background. This result is in line with the prior expectation that Model 4, which features the most human-oriented shown assembly rules, is considered by the majority of the participants to follow more human assembly behavior, cooperates in a premeditated strategy and is accepted accordingly. This assessment result shows a high compatibility between human cognition and Model 4. Model 4 also leads to the highest predictive accuracy (PA) both in the product made from LEGO bricks (PA = 0.87) and the carburetor (PA = 0.69).

When assembling the LEGO product, there are significant differences of the fixation duration, firstly in the interaction between the models of robot behavior and the assembly groups, and secondly in the interaction between the assembly groups and AOI.

The ANOVA for the carburetor makes clear a significant difference of fixation duration for the interaction between the model of robot behavior and the AOI. The most human-like Model 4 is following a more "infallible" strategy than the other models. This can be concluded from the finding of significant differences in both of the above mentioned interactions. Based on the fixation duration data, the conclusion can be drawn that the shortest fixation duration in all experiments occurs for Model 4, which supports the previous findings. Model 4, which is the most human-oriented cognitive simulation model, is feasible to support human-system interaction since the duration of the attention requirements during the assembly task supervision is shorter than for the other models. The most remarkable result in the analysis of the fixation duration is that the carburetor requires more time on tasks than the product made from LEGO bricks. The participant's attention on selecting the next part and carrying out the assembly of the carburetor increases by 100-120% compared to their attention levels when working with the simple LEGO product.

Based on the analysis of gaze behavior, with regard to AOI 3 we can conclude that the carburetor assembly requires more attention than the product made from LEGO bricks. About 50% of the participants experience the necessity to visually inspect the interim state of the work object during the simulation of the assembly sequence on the screen. The frequency of attention shifting from AOI 1 to AOI 3 varies between one and four times for the Indonesian participants and between one and two times for the German participants. In spite of the similar number of participants with the gaze behavior according to type 1 (Table 3.32), the Indonesian participants exhibit a stronger tendency to evaluate the similarity of the actual work object with the simulated object on the screen than the German participants. In this study, the German participants pay more attention to the presented object during the assembly sequence simulation. The Indonesian participants tend to focus more on the relationship between the actual work object and the object presented on the screen. They also show the tendency to want to be more certain about part fitting in the actual work object than the German participants. Thus, the Indonesian participants pay more attention than the German participants with checking on AOI 3 before determining the next part to be assembled.

To conclude, the differences between Indonesian and German persons reported in the research literature are confirmed in this thesis. As reported by Sjahrir et al. (2001), the cognitive function of Indonesian people (especially related to memory recall) is on average decreasing after the age of 40. The study results of Setiati et al. (2011) also indicate that the poorer quality of life experienced by Indonesian people affects the physical and cognitive ability of the elderly. The evaluation of the cognitive functional state of the German participants is confirmed by Sproten et al. (2010). He found that large parts of the older adults' brain are still high functioned (with an intellectually active lifestyle), and even when their cognitive abilities begin to decline, it generally happens at a slower rate. Older persons perceive less information, require longer time to process it and prefer less cognitively demanding strategies; but in general, ageing (especially below 60 years of age) does not affect the cognitive state of the German people. Furthermore, German older adults have a "memory bias" in favor of previous choices that lead to choose coherently with previous decisions and implement fewer changes in strategies (Sproten et al., 2010). The German participants tend to develop a strategy in order to understand the assembly sequences pattern based on their prior experience, which therefore leads to a lower task load and dissatisfaction grade.

6.2 Future Work

The research and study about the cognitive control unit for self-optimizing robotic assembly cells described in this thesis has shown that human cognition can be simulated effectively in a technical system. The results contribute to the improvement of the cognitive compatibility between human and robot. Since the human operator is crucial in the self-optimizing assembly system, the conformity of expectations between human and robot should also be the focus of the future work to support human cognition effectively under varying conditions on the shop floor. Based on cognitive compatible strategies, the human operator can effectively carry out prediction tasks and quickly anticipate the behavior of the robot. However, the studies that were carried out revealed just a small part of the overall existing potential and did not focus on the more advanced applications of a cognitive control unit, meaning that there are various advanced implementations for this technology which have not yet been scientifically analyze. The following topics are, therefore, suggested for the continuation of the study:

- The human-centered design of a pulsed assembly line based on the application of a cognitive control unit in the interconnected work system.
- The automatic acquisition of human-oriented production rules on varying parts of products based on motion capturing.
- The design of age-differentiated work systems, specifically in respect to working persons older than age 50-55 years.
- The design of work systems regarding safety, and the individual learning progress in the assembly cell with human-machine or -robot interaction.
- The development of psychophysiological measures to investigate the influence of the human-oriented design of a CCU in term of stressors, such as taking pupil dilatation, heart rate variability, and saccade width into account.

The aforementioned research topics aim at answering the question of how the cognitive control unit can be effectively designed and implemented in a self-optimizing assembly system with respect to the necessity of a user-centered design. Finally, the user-centered design of a CCU with respect to the flexibility of the self-optimizing assembly systems needs to be investigated further through a comprehensive study design, such as the application of a CCU in self-optimizing assembly systems for multi-variant products.

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