Human-oriented Design of a Cognitive Control Unit for Self-Optimizing Robotic Assembly Cells

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ABSTRACT

This paper presents the human-oriented design of cognitive control unit (CCU) for a self-optimizing robotic assembly cell. The CCU is designed to simulate human cognition, and on the base of prior knowledge, to adapt to the changing conditions in the product structure and material supply. To improve the conformity of the human operator expectations with the technical systems, two experiments focusing on different models of robot behaviour based on the different number of human-oriented production rules in the knowledge base are carried out. The results show that the most-human oriented model leads to the highest performance of the human operator in terms of prediction time, task load and predictive accuracy.

Keywords: robotic assembly cell, cognitive control unit, cognitive engineering

INTRODUCTION

The development of automation in high-wage countries helps producers to meet the customers' need in term of quality and costs, which subsequently leads to several competitive advantages. To further develop these advantages, it has often been intended to enhance labour productivity and reduce personnel expenditure by using articulated robots. However, advanced robotized production systems often require large investments and extensive efforts for configuration and maintenance, without directly adding valued to the manufactured product (Klocke, 2009). Furthermore, the integration of advanced automation technology into the work system is difficult, because the development of knowledge, skills and abilities of the human operator must be ensured and both humans and robots have to work safely and efficient by together (Schlick et al., 2009).

To provide a theoretical foundation for this problem, the role of the human operator in the automated work system must be analyzed. The extended definition of automation by Mayer et al. (2012) describes that "human labour" 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 intervene whenever errors occur. Hence, the future manufacturing systems should focus on the integration of the human operator in the production environment according to his or her particular capability in problem solving and innovation (Schlick et al., 2002). The need for the development of experienced machining operators' skills and knowledge encourages the design and application of more ergonomic human-machine interfaces (Luczak et al., 2003). Using an ergonomic human-machine interface, the human operator can easily evaluate the current situation and state of the system, breaking the vicious cycle of automation (Onken and Schulte, 2010). The human worker should be considered as an integrated part of automation, leading to joint cognitive system (Hollnagel and Wood, 1999) in which the technical function and human operator skills act as one combined system.

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The Cognitive Control Unit (CCU) is a new robot control system based on an architecture of human cognition. It is developed as an approach to achieve a better compatibility between the human mental model and the robot knowledge base. It adopts the technical system of seemingly non-value-adding tasks, e.g. low-level control programming of high-expertise workers. The CCU has the ability to replace repetitive, simple, and dangerous tasks of the operators. It represents a rule-based level processing in a production system (Buescher et al., 2012; Mayer et al., 2009). A CCU can autonomously plan the assembly processes and react effectively to ad hoc changes occurring in its sequences, based on a self-developed set of production rules within its knowledge base. This means that CCU plays a vital role in the design of work systems primarily related to self-optimizing assembly processes (Klocke, 2009).

The conceptual development of self-optimization is driven by the necessity of an integrated view on production systems without focusing only on a single element. A self-optimizing system can change and adapt its objective based on the situation at hand. It is able to rely on its simulated cognition to carry out the adaptation. It is (semi-)autonomously capable of planning and of learning from its own experience (Mayer et al., 2008). A self-optimizing production system contributes to the realization of value oriented approaches while increasing planning efficiency, by reusing its gained knowledge in dealing with new production conditions (Hauck et al., 2009). The elaboration of self-optimization aims at the simulating goal-directed human behaviour (Mayer et al., 2011).

To ensure conformity to the operator's expectations during the supervision of the assembly process (Mayer et al., 2008), the first step in the design process is to use motion descriptors to model the familiar repetitive motion of the human hand-arm system for planning and executing the assembly process within the CCU (Gazzola et al., 2007). When performing a supervisory task, the human operator is continually monitoring the activities in the system, and comparing them with his/her mental model. Based on that mental model, expectations for the following activities can be formulated and compared. When the knowledge base of the CCU is extended by integrating production rules based on human heuristics, then the robot's build-up sequence can be better anticipated by the human operator. Moreover, it is better compatible with his/her procedural knowledge of the assembly process and leads to both less error and less stress (Mayer, 2012). A first laboratory study (Mayer, 2012) exemplarily verifies the predictability of robot behaviour with small plastic bricks (LEGO bricks).

This paper contains two studies. The first study is a continuation of Mayer's experiment. It designs and elaborates independent factors of the work system to verify the findings of the previous study, and to improve the compatibility of the work system with human expectation. The independent factors are different models of robot behaviour for assembly, different kinds of assembly information, different kinds of assembly group, and participants groups. The consistency of human assembly strategy in self-optimizing assembly system is studied further regarding to the transfer and adoption of the human behaviour in the technical system.

The second study deals with the transferability of the assembly strategy of the abstracted product setting into a real manufactured product, a carburetor. The objectives are replicating the first study results and transferring the human-oriented designs from a model to a real product. This second study is designed based on the different models of the robot behaviour, different kinds of assembly groups, cultural background and different ages.

The aim of the studies is to investigate the conformity of robot behaviour with the human operator's expectation in human-robot interaction. She/he has to predict the next action of the robot when assembling the product based on an observed build-up sequence using a virtual reality simulation. It is hypothesized that the more human-oriented production rules are encoded in the knowledge base of the CCU, the shorter the prediction times, the lower the task load and the higher the predictive accuracy for both the LEGO model product and the carburetor.

HUMAN-ORIENTED DESIGN OF THE KNOWLEDGE BASE OF THE COGNITIVE CONTROL UNIT USING A SIMPLIFIED ASSEMBLY REPRESENTATION (EXPERIMENT 1)

Method

Experimental Design and Variables

The experimental design is established by considering four independent variables, namely different models of robot behaviour for assembly task, various assembly groups, kind of assembly information and participant groups.

There are four models of robot behaviour for assembly tasks. Model 1 (the least human-oriented model in terms of the lowest number of human-oriented production rules) acts as the reference model. This basic model of robot behaviour contains only the essential motion elements and sequences based on the popular Method-Time Measurement/MTM-1 taxonomy. Human-oriented procedural knowledge about the assembly task is not included. However, this simulation model is capable of performing all physical possible assembly sequences. Model 2 represents a linear combination of the vicinity of the neighbouring parts and the build-up in layer rules. Model 3 represents a combination of neighbourhood and layer rules in a strong relationship which allows only neighbouring parts within layers. Model 4 (the most human-oriented model in terms of the highest number of human-oriented production rules) characterizes the full adoption of human assembly motion patterns in the assembly sequence.

Three assembly groups are provided in this experiment for the robot to work with. For every completed assembly group, there are two interim states representing human assembly behaviours (see Figure 1).

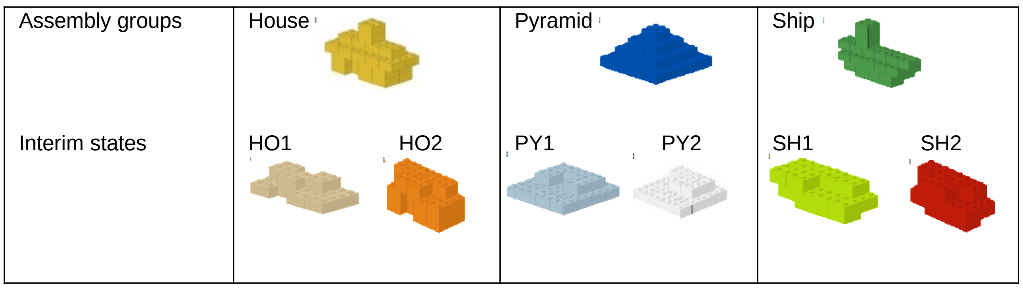

Figure 1. The assembly groups and their interim states in experiment 1.

The number of parts being shown in the assembly sequence history in Experiment 1 is respectively five and seven. The number of five parts shown in the sequence history -known as Corsi Span- is chosen based on the limit of human capacity regarding short-term memory (Corsi, 1972). A number seven parts is selected as a variation from the above mentioned five-part example as well as for a further examination of human limit capacity with regard to an increasing number of assembly information.

Experiment 1 divides the participants into two different groups according to their culture backgrounds. They are European and Asian.

The dependent variables in experiment 1 are the prediction time for performing a correct prediction (as an objective measurement) and the task load assessment (as a subjective measurement).

Procedure

In the first phase, the participants fill in their personal data (e.g., age, level of education, and prior experience on the assembly task as well as LEGO assembly) that is anonymously collected. After completing the personal data, the participant is introduced to the apparatus and the experimental environment. Next, the participant is shown a virtual simulation of an assembly task completed by a robot with the explanation about the sequence on the computer monitor. The participant is expected to recognize the robot's work pattern in the sense of the assembly sequence of the LEGO bricks. The participants must then predict the next brick position using the real object after the robot finishes an interim state assembly. The NASA-Task Load Index/NASA-TLX method (Hart, 2006) is used to evaluate the task load of the participants.

In the experiment, 48 predictions are conducted in four sessions (12 tasks each) with random order of the robot behaviour model and the interim state.

Participants

The total number of participants is 50 participants (15 females and 35 males) with age range of 20-40 years. The participants grade their assembly experience with an average score of 2.3 (SD = 1.4) ranging from 1(low) to 5 (high).

Hypotheses

The following null hypotheses (H_{0i}) are formulated:

- The model of robot behaviour (H_{01}), the assembly groups (H_{02}), the number of parts in the history information (H_{03}), and the cultural background of participants (H_{04}) do not significantly influence the prediction time.
- The model of robot behaviour (H_{05}), the assembly groups (H_{06}), the number of parts in the history information (H_{07}), and the cultural background of participants (H_{08}) do not significantly influence the task load of participants during the experiment.

A Kolmogorov-Smirnov test is used to examine the normality of data, whereas Levene's test is used to examine the homogeneity of variances. Both tests have not shown significant deviation ($p > 0.05$), thus an analysis of variance (ANOVA) is conducted to test all hypotheses with a level of significance of $\alpha=0.05$.

Results and Discussion

Prediction Time

The ANOVA test result for the prediction time data shows that the *p*-values for the models of robot behaviour ($p \leq 0.001$) and the assembly group ($p \leq 0.001$) factors are less than 0.05. Therefore, both corresponding null hypotheses (H_{01} and H_{02}) are rejected. The *p*-values of other factors exceed the threshold of 0.05 ($p = 0.214$ for the history factor and $p = 0.456$ for the culture factor). Thus, the corresponding null hypotheses (H_{03} and H_{04}) are accepted.

Figure 2(a) shows that Model 4 –the most human-oriented model- yields the shortest prediction time. This finding indicates that the most human-oriented model in terms of the highest number of human-oriented production rules (i.e. Model 4) improves the predictability of the assembly strategy pattern and the conformity of the human operator with the technical system. Figure 2(b) shows the error bar chart of the prediction time for each interim state. PY2 and SH1 lead to the shortest prediction time, whereas HO1 yields the highest prediction time. These findings describe the human tendency to the learning process of the assembly strategy by the interim states design. Human tends to learn more easily in a strategy pattern based on the peculiarity of the interim states toward the completed object design. For example, the HO1 design is more difficult to be conceived as a part of house object than the other designs because it only has the first two of the 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 neighbourhood rule is explicitly patterned in this interim state. PY2 and SH1 have the same design so that the participants experience and learn the strategy more often in this design compared to 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.

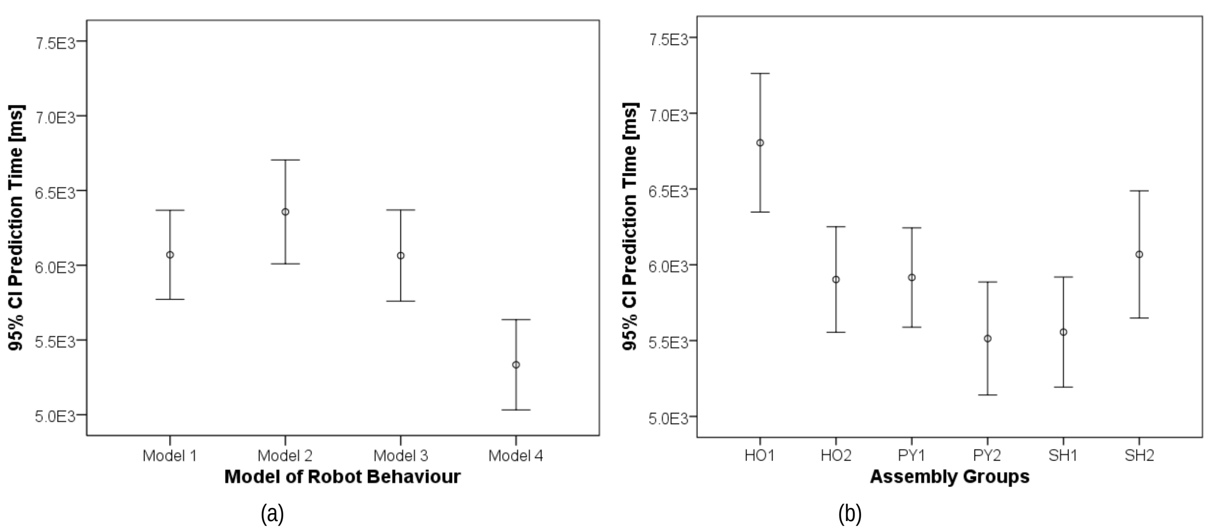

Figure 2 The error bar chart of the prediction time for the four different models of robot behaviour (a) and the six different interim states (b).

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Task Load

The ANOVA test result shows a significant difference of task load for the different models of robot behaviour (p = 0.035). Hence, H_5 is rejected. On the contrary, H_6 (p = 0.642), H_7 (p = 0.392) and H_8 (p = 0.285) are accepted. Figure 3 shows the error bar chart of the task load with 95% confidence interval depending on the model of robot behaviour. The participants working with the most human-oriented model in terms of the highest number of human-oriented production rules (i.e. Model 4) experience lower task load than other models.

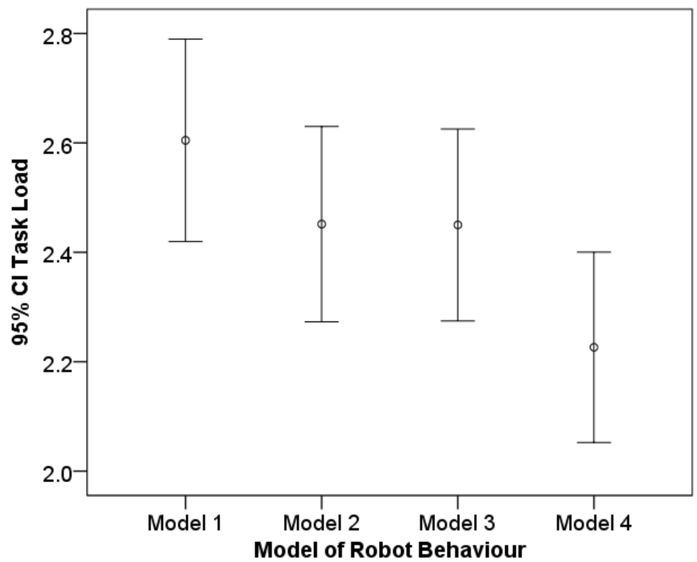

Figure 3 The error bar chart of the task load for the four different models of robot behaviour.

Predictive Accuracy

The predictive accuracy is defined as the relative frequency of the correct prediction. The chi-square test is conducted to statistically analyze the predictive accuracy of the robot behaviour model. The chi-square test result is as follows: $\chi^2(3) = 139.482$, $p \leq 0.001$. The chi square result indicates significant differences between models of robot behaviour in the predictive accuracy. Figure 4 shows the error bar chart of the predictive accuracy with a 95% confidence interval for the four models of robot behaviour. Figure 4 shows that Model 4 with the most human-oriented model in terms of the highest number of human-oriented production rules leads to the highest predictive accuracy (mean = 96.7%, SD = 3.0%), i.e. 96.7% of the expected brick positions are predicted correctly and only 3.3% incorrectly. This finding indicates that the human behavioural patterns contribute to a better predictability of assembly strategy.

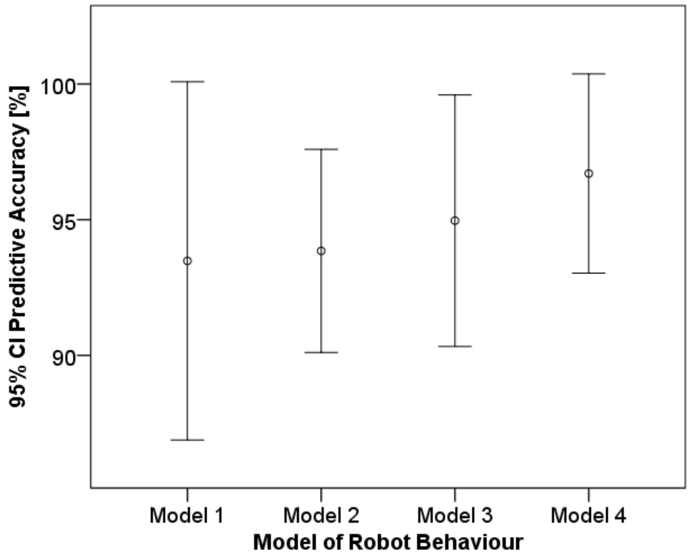

Figure 4 The error bar chart of the predictive accuracy for the four different models of robot behaviour.

TRANSFERABILITY OF HUMAN-ORIENTED DESIGN OF THE KNOWLEDGE BASE OF THE COGNITIVE CONTROL UNIT (EXPERIMENT 2)

To validate the results of experiment 1, experiment 2 is conducted to examine whether the investigated rules to ensure human operator conformity can be used to reduce the prediction time and the task load related to an actual manufactured product.

Method

Experimental Design and Variables

The experimental design is based on four factors, namely the different models of robot behaviour, kinds of assembly groups, the cultural backgrounds and the age of the participants. Three different models of robot assembly based on the production rules are adopted from experiment 1 (Model 1, Model 3 and Model 4). Model 2 is not included in study 2 because of the insignificant difference with Model 3 based on the result of study 1. Additionally, Model 3 is closer to the human strategy rather than Model 2. Hence, Model 3 is selected to examine the consistency of predictions. Two products are evaluated, namely (1) products made from LEGO bricks as before and (2) a carburetor (see Figure 5). The cultural background of the participant groups includes German and Indonesian participants whereas the participants are also divided by age into a younger group (20 – 40 years) and an older group (41 – 60 years). The dependent variables in the second experiment are the prediction time of performing a correct prediction (as an objective measurement) and the task load (as a subjective measurement) as before.

No	Product	Completed assembly groups	Interim State

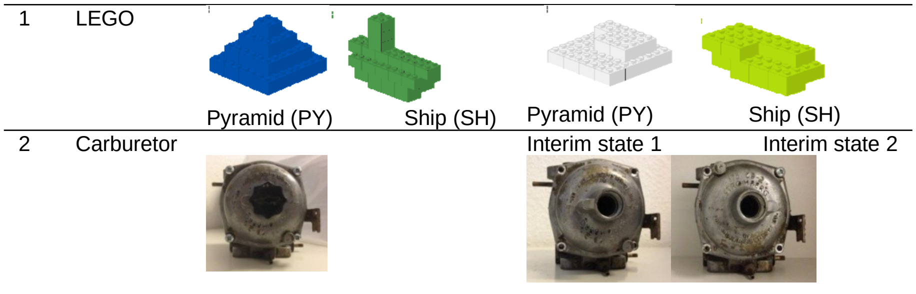

Figure 5 The assembly group and their interim states in experiment 2.

Procedure

The procedure is divided into two main phases: collecting of the personal data and training under the experimental conditions, and the data acquisition. The tasks of the participants are similar to the first experiment. The participant must predict the next brick or carburetor part position using the real object after the simulated robot finishes an interim state assembly. In this experiment, 12 predictions are conducted in two sessions (6 tasks each) with a random order of the robot behaviour model and the interim state.

Participants

The experiment involves 60 participants. There are 30 participants for each cultural background divided into two age groups (15 participants for each age group). The average grade of the participants' assembly experience is 2.5 (SD = 1.1) ranging from 1 (low) to 5 (high).

Hypotheses

The following null hypotheses are formulated:

- The model of robot behaviour (H_{01}), the assembly group (H_{02}), cultural background of participants (H_{03}), and age of participant groups (H_{04}) do not significantly influence the prediction time.
- The model robot behaviour (H_{05}), the assembly group (H_{06}), cultural background of participants (H_{07}), and the age of participant groups (H_{08}) do not significantly influence the task load of participants.

Both Kolmogorov-Smirnov and Levene's test are then conducted to examine the normality of data and the homogeneity of variance, respectively. Both normality and homogeneity tests have not shown significant deviation ($p > 0.05$) for the prediction time and the task load. Thus, an analysis of variance (ANOVA) with a significance level of $\alpha=0.05$ is conducted to test all hypotheses.

Results and Discussion

Prediction Time

According to the ANOVA, for the products made from LEGO bricks, the age *($p = 0.001$)* and model of robot behaviour *($p = 0.005$)* indicate significant differences due to *p-values* of less than 0.05. Based on these results, H_{01} and H_{04}, can be rejected, whereas H_{02} *($p = 0.139$)* and H_{03} *($p = 0.669$)* can not be rejected. Figure 6a shows the error bar chart of the three different models of robot behaviour for the prediction time, whereas Figure 6b shows the error bar chart for the age factor. As shown in Figure 6a, Model 4 with the most human-oriented model in terms of the highest number of human-oriented production rules results the shortest prediction time, whereas the younger group in Figure 6b performs with a shorter prediction time than the older group.

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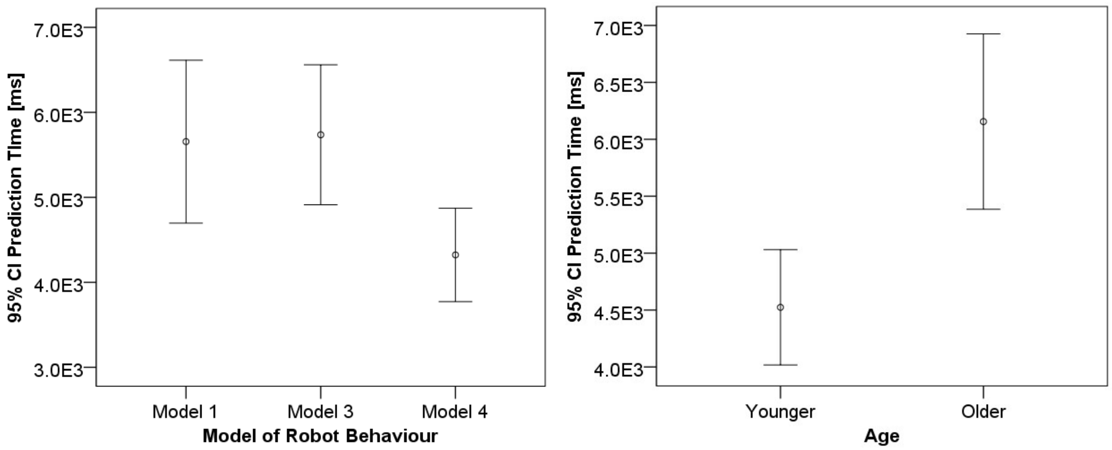

(a) (b)

Figure 6 The error bar chart of the prediction time for the model of robot behaviour (a) and age (b) in the products made from LEGO bricks.

Regarding the carburetor, the *p-values* of assembly group *($p = 0.183$)*, age *($p = 0.502$)* and culture *($p = 0.213$)* exceed the threshold value of 0.05, so that the corresponding null hypothesis (H_{02}, H_{03} and H_{04} for carburetor) are accepted. In contrast, H_{01} can be rejected *($p = 0.000$)*. Figure 7 shows the corresponding error bar chart of the three different models of robot behaviour with 95% confidence interval. Model 4 (which represents the most-oriented human production model in terms of the highest number of human-oriented production rules) results in the shortest prediction time.

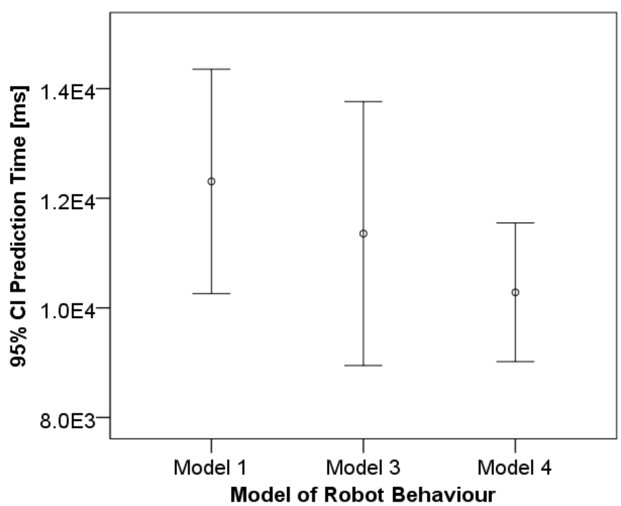

Figure 7 The error bar chart of the prediction time for the three different models of the robot behaviour in the carburetor.

Task Load

Based on ANOVA, significant differences on the task load in the products made from LEGO bricks for culture, age and model factor are found. The corresponding null hypotheses for the culture *($p \leq 0.001$)*, age ($p = 0.005$) and model factors ($p = 0.018$) can all be rejected. However, an interaction between the culture and age ($p = 0.049$) can be confirmed. A descriptive statistical analysis is conducted to show the difference of task load based on the different models of robot behaviour. Figure 8 shows the error bar chart of the task load with 95% confidence interval based on the model of robot behaviour. Model 4 leads to the lowest task load. Additionally, a Bonferroni post hoc test is performed to investigate the pairwise comparison of the culture and age interaction as shown in Figure 9. H_6 *($p = 0.562$)* for the products made from LEGO bricks is accepted, because the threshold of 0.05 is exceeded.

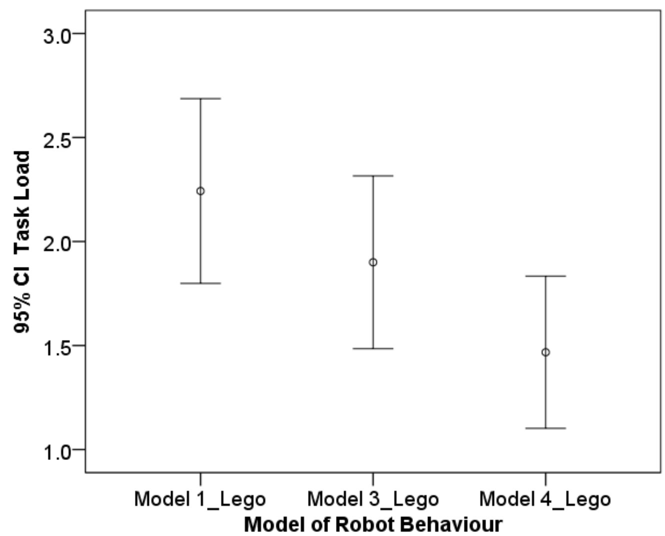

Figure 8 The error bar chart of the task load for the three different model of robot behaviour in the products made from LEGO bricks.

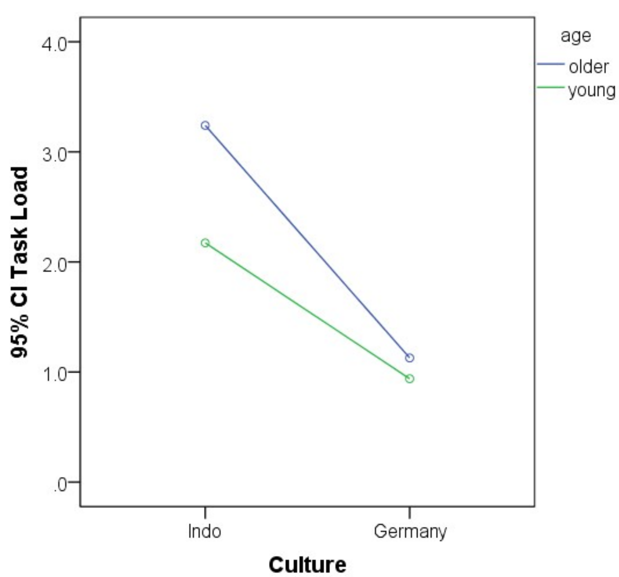

Figure 9 The interaction plot of culture and age for the task load in the products made from LEGO bricks.

According to the ANOVA of the task load in the carburetor experiments, H_{05} and H_{06} are both accepted due to insignificant differences in the model of robot behaviour (*p = 0.929*) and assembly group (*p =0.160*) factors.

A descriptive statistic is then conducted to show the difference of the task load based on the model of robot behaviour in the carburetor product. Model 4 for the carburetor also leads to the lowest task load as seen in Figure 10. Significant differences are found for culture ($p \leq 0.001$) and age ($p = 0.013$) factors. Thus, H_{07} and H_{08} are rejected for the carburetor experiment. The corresponding post hoc comparison is performed as seen in Figure 11(a) and 11(b). The T-test result for the task load in the carburetor experiment based on the cultural factor shows a significant difference (t(179) = 5.591, $p \leq 0.001$). The Indonesian participants experience a higher task load than the German participants. The T-test result for the age factor also indicates a significant difference (t(179) = -2.447, $p = 0.015$), in which the younger group experiences a lower task load than the older group.

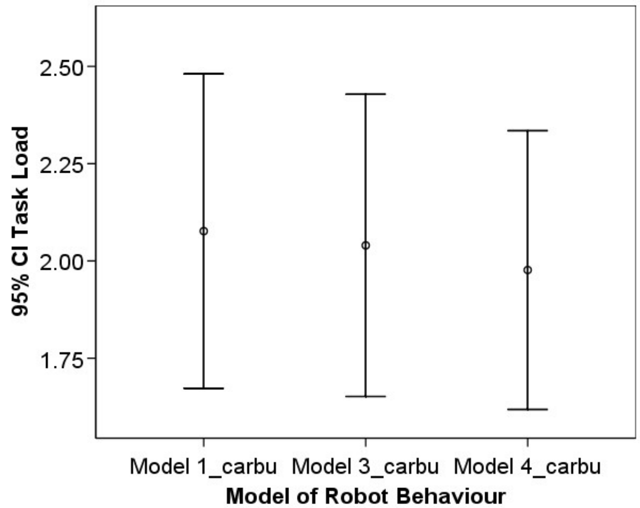

Figure 10 The error bar chart of the task load for the three different models of robot behaviour in the carburetor.

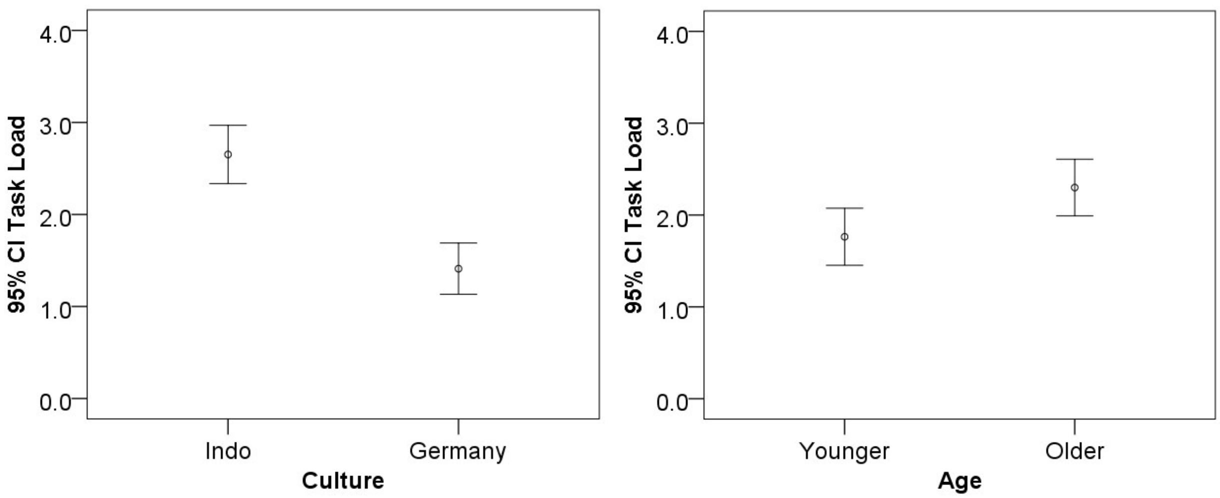

Figure 11 The error bar chart of the task load for culture (a) and age (b) factors in the carburetor.

Predictive Accuracy

The predictive accuracy data is analysed statistically by using a chi-square test for the model of robot behaviour factor. The chi-square test results are $\chi^2(2) = 53.336$, $p \leq 0.001$ for the products made from LEGO bricks and $\chi^2(2) = 24.364$, $p \leq 0.001$ for the carburetor. Figure 12 shows the respective error bar chart of the predictive accuracy with a 95% confidence interval. Model 4 is pointed out as the model with the highest predictive accuracy for both the products made from LEGO bricks (mean = 98.4%, SD = 1.5%) and carburetor products (mean = 96.1%, SD = 1.3%)**.**

(a) (b)

Figure 12 The predictive accuracy for the three different models of robot behaviour in the product made from LEGO bricks (a) and the carburetor (b).

CONCLUSIONS AND OUTLOOK

The process of designing a robotic assembly cell for cognitive compatibility requires a cognitive simulation model that can adapt to the environmental changes in self-optimizing robotic assembly cells. The experiments, which focus on the adaptation to the human assembly behaviour in the assembly work system, descriptively and statistically confirm this statement. The robot behaviour that is generated by the most human-oriented model (in terms of the highest number of human-oriented production rules) leads to the highest performance of the participants in terms of shorter prediction times, lower task load and higher predictive accuracy. This paper concludes that the design of CCU based on the most human oriented model maximizes the conformity between the human operator's expectation and the technical system in self-optimizing robotic assembly cells. To improve the understanding of these matters, further studies of affecting factors of the human cognitive system on designing a technical system with human cognitive compatibility for multi-variant products with various assembly lines should be considered.

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