Design of Human Cognitive Model in A Self-Optimizing Assembly Cell: A Case Study of Indonesian

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***Abstract*—This paper presents a continuing studies of the human cognitive aspects application in the technical systems. The last studies design a human-centered design based on the German culture and the result show a difference significant of human performance between German and Indonesian. Therefore, this study examines the human cognitive model based on Indonesian culture to investigate whether the different cognitive model based on culture aspect affects the human performance. The study was conducted on 60 people classified by age, young (16-34 years old) and old (> 34 years old). Participants render predictions on assembly activity for two interim states of two different types of products which are the Builderific brick and the Pulley Release based on four types assembly model (Reference, Combination, Human Behavior 1, and Human Behavior 2). The dependent variables are prediction time, mental workload and predictive accuracy. The results show that the models of robot behavior and the products have significant influences on mental workload and predictive capability. The age variable significantly influences mental workload, performance and prediction capabilities.**

Keywords—cognitive engineering; Indonesian; assembly

I. INTRODUCTION

Automation is the use of mechanical and/or electronic equipment to replace the human role [2]. Automation using robot application is one of many ways to survive in the competition of production system. Reference [4] explained that the human role in the automation work system can not be replaced. Human is an important factor in the production system, especially to handle control and supervision tasks or to intervene when error occur.

In the study of [10] that comparing prediction time, mental workload and accuracy prediction, it was known that Indonesian had a higher mental workload than German in the prediction task on carburetor and LEGO assembling. Reference [7] explained that along with the increasing stress, there occurs the randomization concentrations against relevant aspects of a job that is caused by individual factors subject. The factors are motivation, fatigue, skill level, temperature, noise, vibration, and comfortability. Most of these factors affect the performance of the subject directly, if they arrive at a high level. Therefore a manufacturing system that focuses on the integration of human factors in the production environment according to their ability in the problem solving and the innovation. The robot application designers must not only be able to visualize the design, but also must be able to develop a solid understanding of the fundamental problems in Human-Robot Interaction (HRI) [3].

Design of the cognitive compatibility plays an important role in these complex systems work primarily to improve a balance performance and optimization between man and machine, or more specifically the interaction of humans and robots. Therefore, the issues raised in this research is the need for analysis of the factors that affect the interaction of humans and robots to produce an ergonomic work system. A self-optimizing assembly cell is designed to represent the interaction between human and robot as well as to model the human cognitive aspects of the technical systems in the production system based on the cognitive system of Indonesian worker [5]. This study examines the human cognitive model based on Indonesian culture to investigate whether the different cognitive model based on culture aspect affects the human performance.

The aims of this study are to identify the independent and dependent variables as factors in the system assembly work on the human-robot interaction, to investigate and analyze the influence of the independent variables and the dependent variable, and to provide the recommended factors in the assembly work system based on the result of the research.

II. METHOD

A. Procedure

This study begins with the encoding and selection of human assembly strategy to be applied to technical systems. The research phase continued with the application of the human cognitive model as production rules for the different type of product. An empirical studies and environmental design of experiments then taken into account. The conceptual model of this research can be seen in Fig. 1.

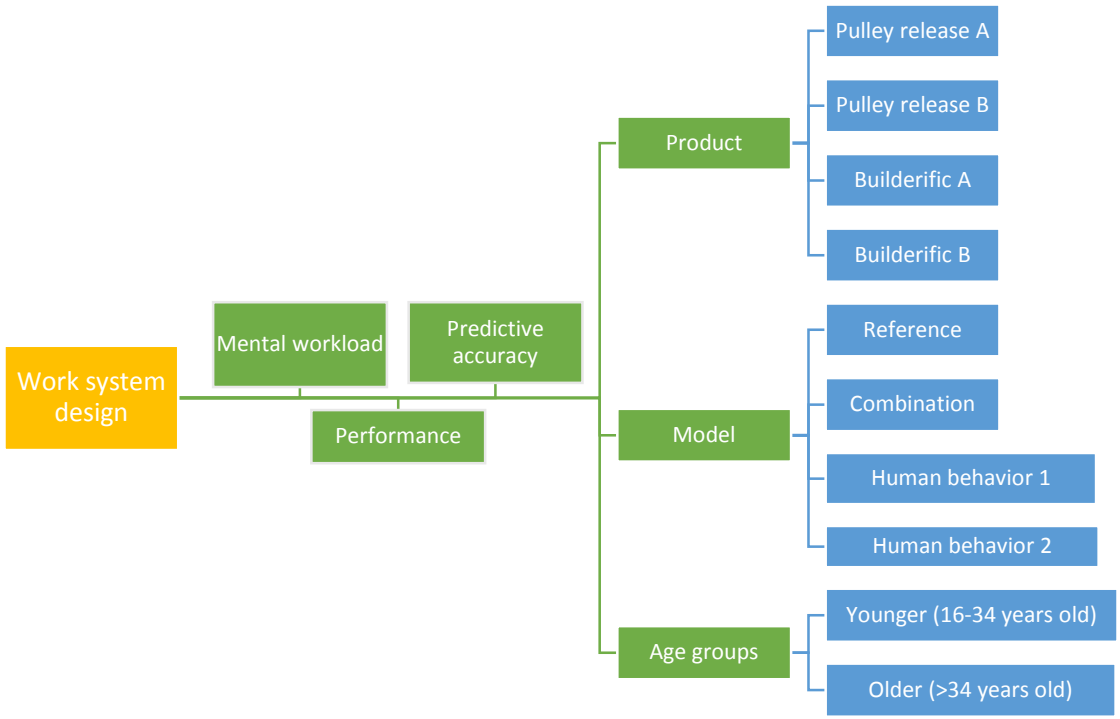


Fig. 1. Conceptual model of the research

To achieve the objectives of this study, it is necessary to encode the human cognitive model represented in the stages of assembly work. This model are transferred into a virtual robot as the behavior of the robot. In this study, the virtual robot only visualized as a series of assembly sequences. The results of the coding was then applied in the production rules (rule assembly) which were used in the research. The participant tasks were predicting the subsequent assembly sequence based on the interim state of the product and the production rules. The tools used and the design of environmental for this prediction study can be seen in Fig. 2. and Fig. 3. The collection of personal data was conducted anonymously including age, last education, work and the level of assemble. The level of assemble ability was using a Likert scale of 1-5, where the value 1 stated level assembly capabilities are very poor and 5 stated assembly capabilities very well. Once the data was loaded, the participants were introduced to the equipment and research environment. In the data collection phase, participants were shown a series of sequence assembly process performed by the robot virtually. For each product (Brik Builderific and Pulley Release) participants were shown five assembly sequences. Participants were expected to remember the sequence assembly and to understand the work patterns of the model in order to determine the behavior of the robot when the robot assembled. After that, participants must predicted the next location of brick Builderific or subsequent product section (sixth assembly sequence) and assembled them into products directly. After conducted assembling activities, participants fulfilled a questionnaire regarding the workload. During the assembly, the participants' activity was recorded using a video recorder the analysis requirements of the accuracy of the prediction time.

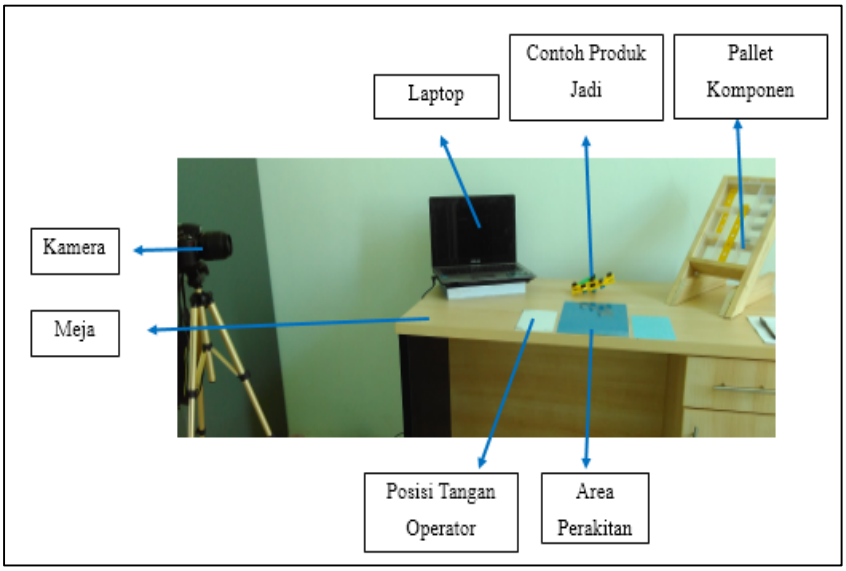


Fig. 2. The equipment of the study

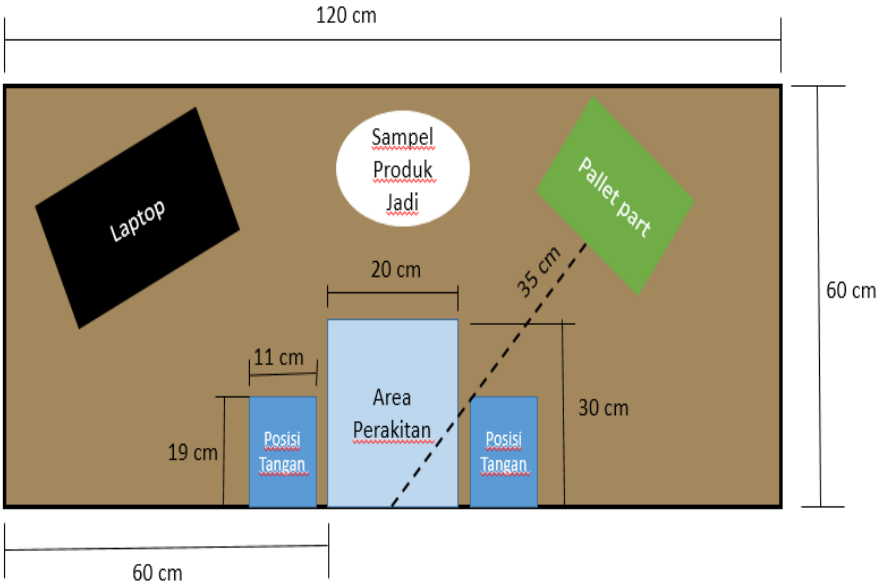


Fig. 3. Design of empirical study environment

B. Research Variables

The dependent variables in this study were the performance, the predictive ability, and mental workload of human operators. The independent variables included in this study were the different models of the robot behavior based on the used production rules, the different types of products (Brik Builderific and Pulley Release), and the age group of participants.

There were three models of the behavior of robots developed by [4] i.e., reference models, combination, and human behavior in LEGO assembling. Reference model was represented on the order of assembly that done freely and randomly. The combination of the model was a combination of a layered assembly model and neighborhood rules. In human behavior 1 model, the sequence of the assembly was designed based on human behavior. To human behavior II models, the assembly sequences was designed based on the small-scale observations of seven respondents when assemble Pulley Release and Builderific.

There were 2 products used in this research: Builderific and Pulley Release (see Fig. 4). For each product, there were two interim states symbolized by A (interim state 1) and B (interim state 2). Length of the initial sequence (which is displayed on the virtual robot) was five assembly sequence. Five sections are shown in a sequence known as Corsi Span of the research results Corsi (1972) [10], which are selected based on the human capacity limit short-term memory for processing visuospatial information on Corsi-Block Tapping Test.

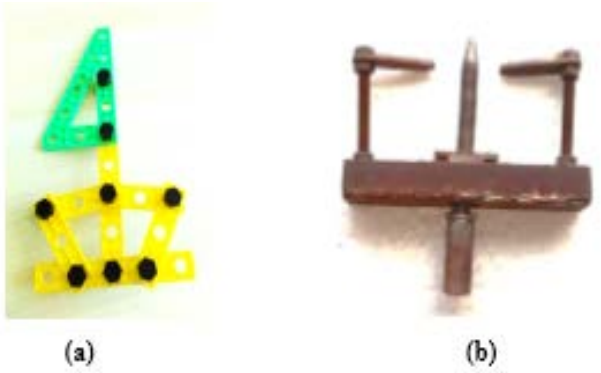


Fig. 4. a) Brik Builderific (b) Pulley Release

The age group of the participants was divided into two groups, namely young age (16-34 years) and elderly (> 34 years). The age classification is based on the study of [1] that stated an assembly capability peak is at the age of 16-34 years.

The total number of participants in this study were 60 people [8] with the age range of 16-55 years. The average value of the ability and experience to assemble amounted to 3.3 (SD = 0.79) for old age (> 34 years) and 3.1 (SD = 0.63) for the younger age (16-34 years) with a scale of 1 (bad) - 5 (Very Good). The hypothesis (H_0) used in this study were:

- Model the behavior of the robot (H_{01}), product type (H_{02}) and age (H_{03}) significantly affect mental workload.
- Model the behavior of the robot (H_{01}), product type (H_{02}), and age (H_{03}) significantly affect the performance
- Model the behavior of the robot (H01), product type (H_{02}), and age (H_{03}) significantly affect the predictive accuracy

III. Result and Discussion

A. Mental Workload

Mental workload is workload received by workers after doing a mental work. Mental workload can be the extent to which the level of expertise and performance of the individual with other individuals [6]. Human mental functions is dedicated to process the information such as perception, attention, memory and problem solving [9]. In order to determine the level of mental load operator in performing prediction task when assembly a product, this study used the help of a questionnaire which is an adaptation of the NASA-TLX questionnaire. The three indicators used in this study were Mental Demand (MD), Temporal Demand (TD), and Own Performance (OP). Those three indicator were selected because the assignment of the operator was simply only predicting the next assembly sequence for each product. The study was also conducted in the short assembly time so it was not to cause physical fatigue (Physical Demand), excessive effort (effort) and frustration (frustration Level).

The results showed that the data was not normally distributed ($p \leq 0.001$) and not homogeneous ($p=0.003$). Because the data performed an unqualified assumptions for analysis of variance (ANOVA), then the data was entered into the non-parametric category. Furthermore, the Kruskal-Wallis test was done to determine the influence of model, products, and the age variables. The results showed that the three variables has a value Sig. <0:05, so they had significant influences on the mental burden.

1) Analysis of Model Variable

The results of this study was comparable with the results of [4] which stated that there were significant differences in the chronologically structured of workload data on the model of the robot behavior as the main variable. The test results of Mann Whitney U as a post hoc test for mental load showed that the comparison between the reference model with three other models (Reference-Combination, Reference-Human Behavior 1 and Reference-Human Behavior 2) showed a significant effect on the mental workload (Sig. <0.05). It can be concluded that the model Reference was a model that has the most significant influence on the mental workload. It was resulted that the Reference model had the highest mental load value ($\bar{x}$= 31.3440, SD = 1.51830) and the combination model had the lowest value of the mental burden ($\bar{x}$= 19.3935, SD = 0.64365).

Combination models had the lowest value of mental workload among the other models for the Pulley product. This model had an identical form interim state so the sixth assembly sequence was located on a similar place for the interim state A and B, which can be seen in Table 1. In such circumstances, the operators were performed the prediction task with the similar sequences for A and B and by doing so, the learning process was faster than other model.

In the Builderific product, the operator was helped by the design of the interim state. As seen in Table 2, the combination model in Builderific product was focused on the center of the product. This was such as a clue to the operator for determining the predictions of subsequent assembly, thereby reducing the value of mental demand of the operators. It was also based on the principle of a combination models that the assembly tends to complete the operation in one line or first layer. Reference model had the highest value among the other models. This can be caused by the absences of the rules or specific pattern. In contrast to other models that had predictable patterns or rules, reference model required a higher mental demand and temporal demand for predicting subsequent assembly sequence.

2) Analysis of Product Variable

The results of Mann Whitney U test as a post hoc testing for mental load indicated that all the comparison of products had significant influences on the mental workload (Sig. <0.05). To find out the most influential products, a post hoc test was conducted and as the result the Builderific product with interim state A had the highest mental load value ($\bar{x}$=26.8555, SD=0.99011) and the Pulley product with interim status B had the lowest value of the mental burden ($\bar{x}$=18.7659, SD=1.06406). The general analysis showed that average value of the mental workload in the Builderific product was higher than the Pulley product. This can be happened because the Builderific product had a more complicated design and prediction task, a higher number of parts than the Pulley product. For Builderific product, the expected prediction task of the operator in charge was assembled the nuts and bolts, while for the Pulley, the next task was only one step assembly operations. Thus, operators require a higher mental and temporal demand to predict the order of Builderific assembling than the Pulley assembling.

3) Analysis of Age Variable

There were two classifications of age variables used in this research. They were the young (16-34 years) and old (> 34 years) groups. The results of Mann Whitney U test as a post hoc test for mental load showed that age had a significant influence on the mental workload ($p \leq 0.000$). The old age group had a higher mental load ($\bar{x}$ = 25.9918, SD = 0.90576) compared with the younger age group ($\bar{x}$= 20.4400, SD = 0.56037). These results concurred with [1] which stated that the peak level of ability to assemble objects and to understand the arrangement of the image is in the age of 16-34 (a young age) and will decrease after the age of 34 years.

B. Performance

In this research, the performance of an operator was measured by the length of time required to perform the prediction task. The duration of prediction time was obtained from recorded video. Prediction time measurement started when the virtual robot displayed on the laptop screen was stopped and it finished when one of the operators hand back to the starting position. Prediction time was presented in seconds. The results showed that the data are not normally distributed ($p \leq 0.001$) and not homogeneous ($p \leq 0.001$). Because the data was not qualified for analysis of variance (ANOVA), then the data was entered into non-parametric test (Kruskal-Wallis).

From the test results, it was showed that from the three variables only age variable had a significant difference on the performance ($p \leq 0.001$). The results of Mann Whitney U test as a post hoc test for performance showed that age variable had a significant influence on the performance ($p \leq 0.001$).The result also showed that the elderly required a longer prediction time ($\bar{x}$= 64.2808, SD = 0.67465) than the younger age ($\bar{x}$= 59.4363, SD = 0.77900). Thus it can be said that the performance of the younger age in the prediction task was higher than the older group of the operator. These results concurred with [1] which stated that the peak level of ability to assemble objects and to understand the arrangement of the image is in the age of 16-34 (a young age) and will decrease after the age of 34 years.

C. Predictive Accuracy

In this study, the predictive accuracy of an operator was measured by the deviation between the expected and observed position of the prediction location [10]. To complete a product assembly, the process taken 8 sequences into account, and the assignment operator only to predict the sixth position of the brick or product part. So in this study, an operator had a success prediction task if the expected and observed position is similar. The results showed that the data are not normally distributed ($p \leq 0.001$) and not homogeneous ($p \leq 0.001$). The data was unqualified for analysis of variance (ANOVA), then the data was tested using the non-parametric category. Furthermore, the Kruskal-Wallis test was done to determine the influence

of model, products, and the age groups on the prediction capabilities. From the test results, it was found that the three variables had value of Sig. <0:05, so that these three variables had influences on performance.

TABLE 1. INTERIM STATE AND THE ASSEMBLING SEQUENCES FOR COMBINATION MODEL (PULLEY)

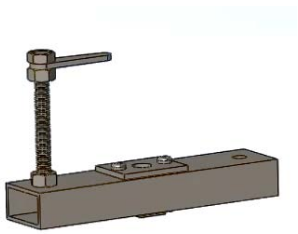
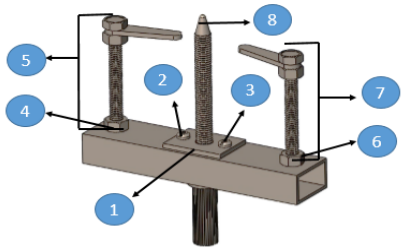
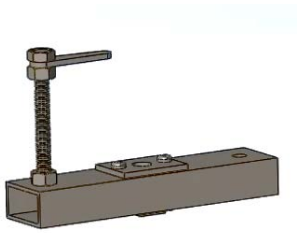
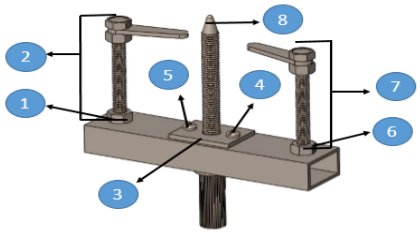
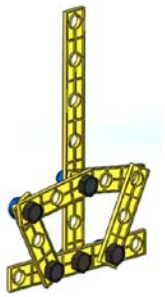
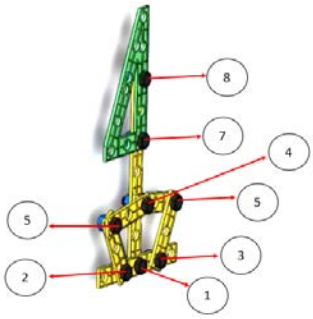
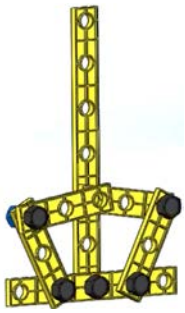
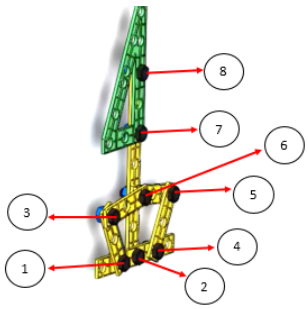
	Interim State	Assembling sequences
Combination Model Interim State A		
Combination Model Interim State B		

TABLE 2. INTERIM STATE AND THE ASSEMBLING SEQUENCES FOR COMBINATION MODEL (BUILDERIFIC)

	Interim State	Assembling sequences
Combination Model Interim State A		
Combination Model Interim State B		

1) Analysis of Model Variable

The results of Mann Whitney U test as a post hoc test showed that almost all models had significant influences on the predictive accuracy of the model except the comparison between Human Behavior 1 to 2 ($p = 0.781$). Thus, among the models of Human Behavior 1 and 2 insignificantly affect the ability of prediction.

The result also showed that the model that had the highest level of accuracy was the combination ($\bar{x} = 80.8333$, SD = 2.54607), and Human Behavior 1 models have the lowest levels of accuracy ($\bar{x} = 58.7500$, SD = 3.18432). Thus, it can be said that the operator had a high predictive capability in product assembly activity with the combination model and of the most difficult model was Human Behavior 1 model. This result answered the question about a lower performance of Indonesian comparing German. It can be said that Indonesian has a different behavior with German in assembly processes represented and model established in German culture was not compatible with the cognitive system of Indonesian.

The combination model had a high degree of predictive accuracy due to the similar reason of the analysis of the mental workload (identical design of Pulley and focus of the Builderific on the center. Human Behavior 1 Model, which generated the lowest prediction capability produced the highest number of errors in interim state A especially for Builderific (Table 3). About 83% operator predicted in the seventh position which rendered to a lower predictive accuracy of Human Behavior 1.

2) Analysis of Product Variable

The result of Mann Whitney U test as a post hoc test for the comparison of the predictive ability showed that almost all types of products had significant influences on the predictive ability expect for the comparison between Builderific B and Pulley B ($p = 0.284$). Thus, the Builderific B and Pulley B insignificantly affect the ability of prediction. The result also explained that the product that had the highest levels of accuracy are Pulley A ($\bar{x} = 92.9167$, SD = 1.65946), while Builderific A had the lowest accuracy ($\bar{x} = 54.1667$, SD = 3.22298). Thus it can be said that the operator has a high predictive ability in a prediction task using Pulley with interim state A, while the most difficult product to be predicted was the Bulderific with interim state A.

The value of the predictive ability of the interim state A of Builderific product was lower compared than most other types of products. This is due to the fact that no one of participants from younger group could predict the right next position when using Human Behavior 1 model. 83.3% of them chose the seventh position and 16.7% chose the eighth position. From the result, it can be generalized that there was a tendency of the operator to finish the assembly in a straight line (one line) to then move to the other side. Similarly, the operators of older age group also were rendered a lot of prediction errors when using Human Behavior 1 model. Only 6.7% were successfully predicted precisely. Within Human Behavior 2 model, the older age group render too many mistakes predictions as well. Only 16.7% were successfully predicted the assembly sequence in the sixth position.

3) Analysis of Age Variable

The result of Mann Whitney U test as a post hoc test for the ability of prediction showed that age has a significant influence on the predictive capability ($p \leq 0.001$). The result also revealed that the young age group had a higher level of predictive accuracy ($\bar{x} = 80.2083$, SD = 1.82047) compared with operators who are included in the classification of older age group ($\bar{x} = 69.5833$, SD = 2.10204). Thus, it can be said that the young operators had a better predictive ability compared with the operators in older age group. These results concurred with [1] which stated that the peak level of ability to assemble objects and to understand the arrangement of the image is in the age of 16-34 (a young age) and will decrease after the age of 34 years.

4) Analysis of Predictive Accuracy

Based on the model of the robot behavior, there were three possibilities of predicted the position of the assembly. The result of each model allowed different positions and by doing so each position has the same opportunity. For example, the assembly sequences of the reference model were randomly designed, so the operator had a freedom to fill next position anywhere.

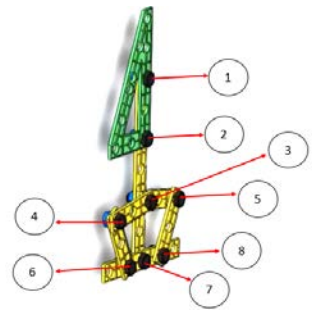
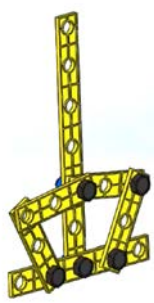
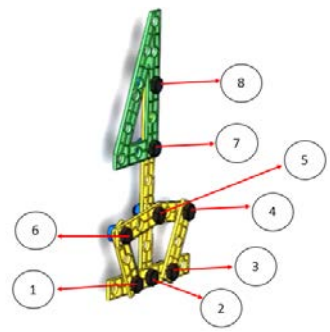
Human Behavior 1 as human-oriented model expected only one right position on the prediction task. Therefore, in this study it can be evaluated which model can be responded effectively and efficiently by the operator as represented in the high accuracy valued.

To measure the proportion of prediction accuracy of operators to four models of the robot behavior, a deviation was defined to represent the difference between the expected position (Expected) and observations (Observed). Each position reference model had the same probability, therefore the proportion of the value of this model is expected to 0.33 for each position. As for the other models, the proportion of expected position were 1 (for the sixth position), 0 (for seventh position) and 0 (for

eighth position). This arrangement was performed based on the production rules of the assembly pattern that only expected one predicted and right position.

After knowing the difference of predictions proportion, then the calculation of predictive accuracy can be taken into account. Fig. 5 showed the highest level of predictive accuracy in Builderific product was belong Human Behavior 2 model (76%). This result meant that Indonesian had the highest predictive accuracy when using model that established based the pattern of Indonesian cognitive model. It also can be meant Indonesian may performed a lower performance than German [10] because there are different pattern or model of cognitive system that configure the production rules in the assembly task. As for the Pulley product, the model that had the highest level of accuracy is the model of Human Behavior 1 is 0.85 (Fig. 6). Additionally. The predictive accuracy can also be seen based on the interim state and the model of robot behavior for each of the products. For Builderific, combination model with interim state B had the highest value (0.80). As for the Pulley, Human Behavior 2 models with interim state B had the highest value (0.97). Despite of the high level of predictive accuracy in reference model, it can not be further analyzed because all position were true.

TABLE 3. INTERIM STATE AND ASSEMBLY SEQUENCES FOR HUMAN BEHAVIOR 1 MODEL (BUILDERIFIC)

	Interim state	**Assembling sequences**
Human Behavior 1 Model **Interim state A**		
Human Behavior 1Model **Interim state B**		

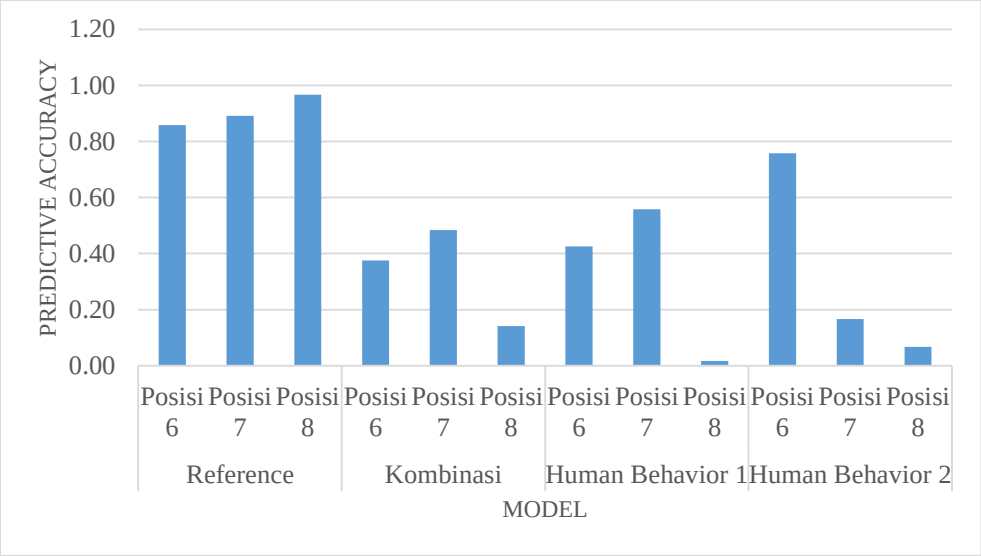


Fig. 5 Predictive accuracy based on the model of robot behavior (Builderific)

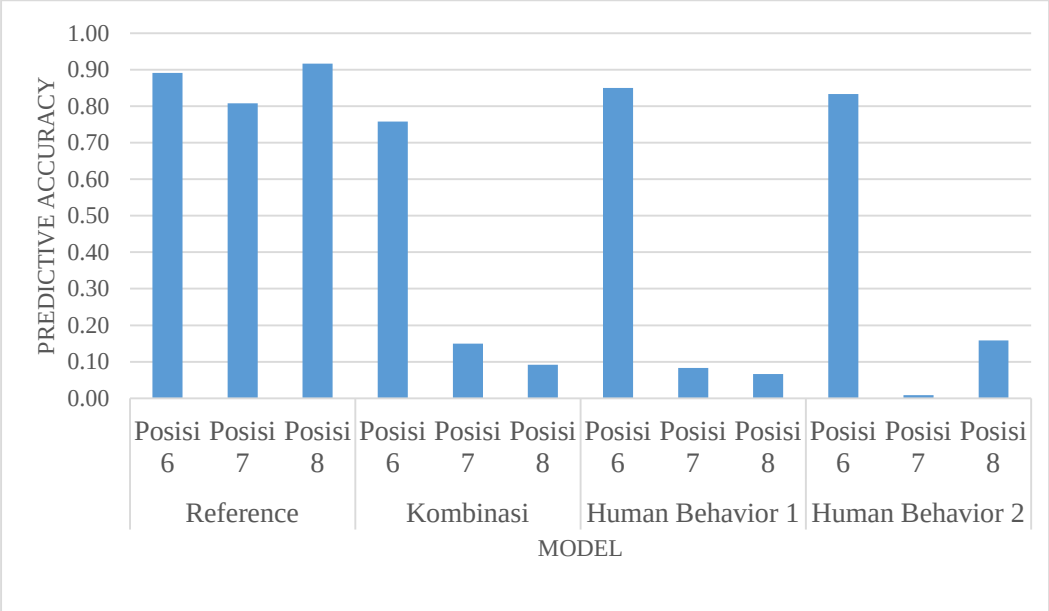


Fig. 6. Predictive accuracy based on the model of robot behavior (Pulley)

IV. Conclusion

Based on the results of collecting, processing, and data analysis, it can be concluded that model of robot behavior and product had an influence on the mental workload and the predictive ability. The age variable had effect against the mental workload, performance and the predictive ability. It also can be concluded that Indonesian prefer work with model Human Behavior 2 that established from cognitive system of Indonesian themselves. So, it can be meant that Indonesian had different pattern of cognitive system compared with German.

The further studies should be analyzed in detail the assembly strategy of Indonesian worker regarding the combination model because some high performances also obtained when they work with this model.

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