HOW CHANGES IN COGNITIVE AUTOMATION CAN AFFECT

HOW CHANGES IN COGNITIVE AUTOMATION CAN AFFECT OPERATOR PERFORMANCE AND PRODUCTIVITY

D. Li, A. Landström, S. Mattsson & M. Karlsson

Chalmers University of Technology, Hörsalsvägen 7A, SE-41296

ldan@student.chalmers.se, annalan@student.chalmers.se

Abstract: To predict system performance, understanding what affects operator performance and productivity is important. This notion was tested in a LEGO experiment including 40 students. After introducing changes in cognitive automation e.g. assembly instructions and material façade, operator performance and productivity was increased. The aggregated results give an indication of how cognitive automation affects the operators' initial assembly performance. Industrial studies are needed to ensure observed trends and to further study the impact of cognitive automation characteristics. The trends however point toward that the perception of cognitive support has an impact on the final assembly.

Keywords: Productivity, operator performance, cognitive automation, non-value adding time, perceived view.

1. BACKGROUND

In today's production systems, the products are prone to be changed or replaced more rapidly with many new variants and models. The continuous changes in the product families make the ramp-up time essential to the productivity and profitability of the production (Lotter, *et al.*, 2009). One reason for the high product variety is mass-customization, which is the strategy to deliver customized products to a cost similar to products that have been mass-produced (Coletti and Aichner, 2011). Mass-customization forces the assembly system to handle high flexibility, small batch sizes, small product volumes and a high number of variants (Heilala and Voho, 2001) at a low cost (Schleich, *et al.*, 2007; Papakostas, *et al.*, 2010). In these systems, human operators remain an essential resource, by virtue of being superior to robots at rapidly interpreting unplanned tasks and situations, and handling flexibility and complexity (Fasth, *et al.,* 2010; Papakostas, *et al.,* 2010). The notion of human importance is especially important in a final assembly context where one third of the manufacturing workers are involved (ElMaraghy, *et al.*, 2010). Since 25-30 % of manufacturing companies' total cost is spent on assembly, costs could be reduced with an increased assembly performance (Bi, *et al*., 2007).

The aim of this paper is to describe how changes in cognitive automation can affect operator performance and productivity. Sanchez (2009) proposed that system performance can be seen as a product of combination support given for automation, how automation is used by the human and the quality. Therefore it is important to study the Levels of Automation (LoA). One way to measure LoA and especially the support given to the operator is by following the definition of cognitive automation by Fasth, *et al*. (2013): "*technical solutions helping the operator, e.g. HOW and WHAT to assemble (Levels 1-4) and situation control (Levels 5-7)"*. In this categorization, based on Frohm (2008), the cognitive LoA ranges from Level 1 to Level 7. Cognitive automation is fundamental to the work tasks since the instructions and the position of the components affect the workers' ability to find and get the components. The workers' understanding of the work situation varies and counter-intuitive localization of information or components may protract the workers' ability to perform. Therefore, it is interesting to study how cognitive automation changes may improve the assembly. Thus, support given by automation and the ways humans use automation is of interest (Sanchez, 2009). There are also dimensions of cognitive automation that can be investigated further.

To measure the overall system performance, a combination of operator performance and productivity should be used (Gunasekaran, *et al.*, 1994; Inman, *et al.*, 2003). Therefore how cognitive automation changes affect the production was studied by measuring:

- Operator performance
- Productivity

To measure operator performance and productivity, two experiment settings were studied: one before and one after cognitive automation changes were done. The goal of this research is to, by studying the experiment situation, find relations and potential improvements that can be used in real-time. Since human individuals perceive information differently, the instructions should be designed carefully with regard to certain principles in order to be a support, rather than an obstacle. Therefore, it is interesting to study how changes in cognitive automation affect the operator performance as well as how it affects the overall system performance.

2. COGNITIVE AUTOMATION AND PRODUCTIVITY

2.1 Cognitive Automation

The concept of cognitive automation originate from Frohm, *et al*. (2008), with this definition of Levels of Automation (LoA): *"The allocation of physical and cognitive tasks between humans and technology, described as a continuum ranging from totally manual to totally automatic".* Fasth (2012) further defined LoA as: '*The allocation of physical and cognitive tasks between resources (humans or technology), described as discrete steps from 1 (totally manual) to 7 (totally automatic), forming a 7x7 LoA-matrix containing 49 possible types of solutions'*. The LoA-matrix can be seen in Figure 1. Each specific LoA-solution is connected to a physical and cognitive LoA. For instance LoA(1,1), where the operator is carrying out a task which is completely manual and has no help cognitive support, e.g. a precise pick-and-place task.

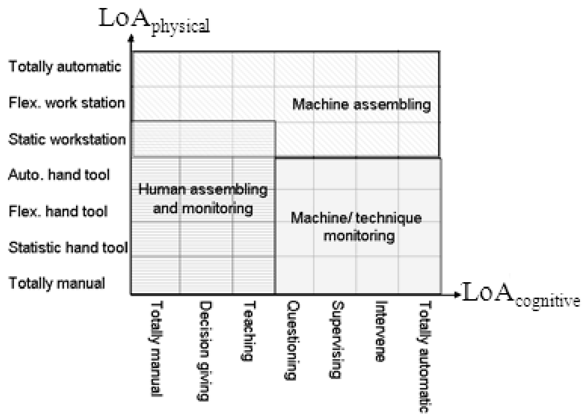

Fig. 1. LoA-matrix showing joint physical and cognitive automation (Fasth, *et al*., 2008).

Cognitive automation was defined as "*technical solutions helping the operator, e.g. HOW and WHAT to assemble (Levels 1-4) and situation control (Levels 5-7)"* (Fasth and Stahre, 2013). The level of cognitive automation seen in the experiment setting are connected to how and what to assemble i.e. assembly instructions and material façade. The instruction could be seen as cognitive automation Level 3 and the façade as cognitive Level 2. Within each of the cognitive LoA-solutions there can be many different types of cognitive support. This includes also different dimensions of the support. For instance although Level 3 is Teaching, this level can be supported by introducing many different types of tools. One example is instructions given on a screen (as in this case) but could also be hand-written or computer written. Depending on what type of instruction it is, the characteristics of the instruction, the quality of it could be interpreted differently. It could be easy to read, there could be figures connected to it or it can be just plain text.

2.2 Productivity

Tangen (2005) reviews several definitions of productivity. Several of these definitions regard the ratio between outputs and required inputs (Bellgran and Säfsten, 2010; Hill, 1993), which is used in this paper. According to Bellgran and Säfsten (2010), this definition of productivity requires that all activities in a production system needs to contribute to the output in order to be considered as value-adding instead of waste. Therefore, productivity is interesting when the progress of resource efficiency can be studied for a period (Bellgran and Säfsten, 2010).

Further, Bellgran and Säfsten (2010) elaborate that different amount of factors can be used in order to describe the productivity:

- partial productivity, which only include one single factor
- total factor productivity, several factors are included
- total productivity, all factors are included

Partial productivity is the easiest to calculate, due to that it only takes one factor in account (Bellgran and Säfsten, 2010). However, Bellgran and Säfsten (2010) argue that this approach may provide a deceptive perspective of the issue, since only one factor is accounted for. In order to make a better analysis, comparisons between more factors are required, but it becomes difficult to fairly balance the importance of the input values and to properly define the input and output values (Bellgran and Säfsten, 2010).

This study used partial productivity, comparing the amount of value-adding time with the total assembly time. Using time for measuring productivity simplifies comparisons since it independent of different financial frameworks and currencies (Bellgran and Säfsten, 2010). However, value-adding time may appear subjective depending on the efficiency of the value-adding work.

Lean conceptualizes seven types of waste in order to improve the productivity of production systems. Hicks (2007) divide all activities into value-adding and non-value-adding, which is considered waste. The wastes are overproduction, waiting, transport, extra processing, inventory, motion and defects (Hicks, 2007). In this specific research, where only one assembly station is studied instead of an entire production system, four wastes are especially interesting to study:

- Extra processing
- Inventory
- Motion
- Defects

3. METHODOLOGY

Two experiments were carried out in a simulated assembly station in the Production System Laboratory at Chalmers University of Technology. Test persons were recruited from some undergraduate programs, they were equally divided between men and women. The product assembled in the experiments was a gearbox in LEGO, see Figure 2.

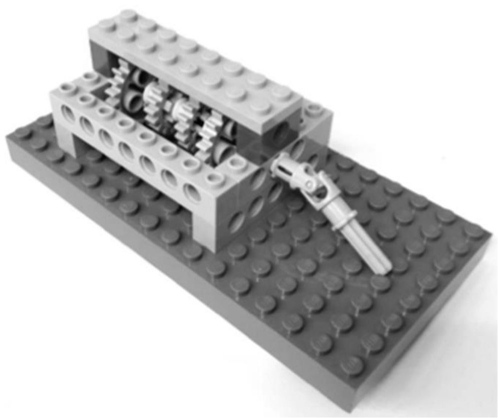

Fig. 2. A gearbox of LEGO blocks.

The study was divided into two sets of experiments where the participants assembled the same product. In the first set the original material façade and instructions were used, 30 participants tested these settings, Figure 3. The results from the first set were analysed and based on the results, new instructions were created and a redesign of the material façade was implemented. The new instructions were created using the design principles suggested by Bellgran and Säfsten (2010). For more information about the changes in the instruction, see the paper *Simple Guidelines That Improve Operator Performance* by Johansson, *et al*. (2014). Ten new participants, that didn't participate in the first set, tested the new assembly instructions and material façade. The results from the second experiment set were compared to the result of the first set in order to study the impact of the changes.

Fig. 3. The experiment area and the experiment set-up.
1. Instructions, 2. Takt time, 3. Material façade, 4. Assembly ground plate

Each participant was given a verbal description of the experimental proceedings and asked for oral consent to participate. Participants filled in a background survey to provide the age, educational level and previous experience with LEGO blocks. The participants had as much time as they desired to go through the instructions before starting assembling.

The different takt times were short, 50 and 70 seconds. All participants assembled five cycles with each takt time, where a product was assembled per cycle. In the first experiment set the takt time order varied between each person, in the second experiment set the shortest time was always used before the longer, see Table 1. Between the different takt times and after the whole experiment an interview was conducted to collect data about how the participant felt about the instructions and the material façade. The aim of the experiments was to investigate the operators' performance and experience, improve the settings in the assembly station and evaluate any differences in performance or experience after the change.

Table 1. Experiment set-up, number of participants and takt times used.

Experiment	Number of participants	Takt time order, A = 50 seconds, B = 70 seconds
Exp. 1	30	AB or BA
Exp. 2	10	AB

All participants were filmed during the experiment and each assembled part was recorded as assembled correct or with error, i.e. all parts not assembled according to instructions. This way of counting the number of errors implies that errors are not exclusive and each product assembled can have several errors.

3.1 Measuring operator performance and productivity

The performance was measured by the Number of Parts Assembled Correctly (NPAC), calculated from number of assembled parts and the errors, equation 1. This calculation was also made for each set of assembly cycles, five assemblies with a takt time, equation 2.

$$NPAC = NPA - NE \quad (1)$$

$$NPACi = \sum_{1}^{n}(NPAi - NEi) \quad (2)$$

Where;
NPA – Total number of parts assembled
NPA_i – Total number of parts assembled for cycle i, for i 1 or 2
NE – Number of errors made
NE_i – Number of errors made for cycle i, for i 1 or 2
n – Number of participants for each experiment set, n=30 for set 1 and n=10 for set 2

To be able to compare the efficiency in assembly between the two experiment sets, the time it takes to assemble one part correctly, s/NPAC, was calculated. This was done by dividing the takt time with the NPAC result from the experiment cycle. Then an average of the s/NPAC for participants in set 1 and 2 was calculated for comparison.

To determine the productivity, video recordings of all experiments were studied to determine how much of the assembly time was value adding and how much was not. The assembly was divided into tasks such as "get cogwheel" and "assemble cogwheel on axis", these tasks were determined as value adding or not. To determine how long time each task takes to perform a software tool, able to step through the movie in steps of 1/100 seconds, was used. This procedure was also used to analyse the material façade. Productivity was calculated as the ratio between the value adding and non-value adding time.

4. RESULTS

The cognitive automation changes were based mainly on results of the interviews and observations. These results were combined with the most common assembly errors. Interviews showed that the participants found the instructions generally good, but many improvement suggestions were given. Some participants perceived the instructions as unclear, which could be due to small pictures, and some participants thought that certain information was unnecessary. The information was presented in several steps instead of summing it up in one picture. Also, irrelevant information could be removed. A further description of how the instructions were analysed and changed can be seen in (Johansson, *et al*., 2014). Two thirds of the participants thought that the material façade was bad. In general, the perceived view was varied; some issues could be experienced as both good and bad depending on the participants. A majority of the participants however, thought that the placement of the three different cogwheels should not be placed next to each other. Many thought that the sequence of components should follow the order one assemble them, and that it was difficult to see the content of the boxes.

The most common errors are presented in Table 2. Because the common errors were connected to incomplete assemblies or wrong placements of components changes were made to the instructions and material façade.

Table 2. Most common assembly errors.

Type of error	Percentage	Explanation
Non-assembled axis	66.88 %	The axis assembly has been started but not fully assembled (not attached to the gear box)
Wrong placement of gear box on ground plate	49.38 %	The gear box was placed at a place not stated in instructions
Plugs under the ground plate	6.25 %	Two plugs, instead of one were placed under the ground plate
One or several pieces were missing on the axis	5.31 %	Pieces have been placed on the axis wrongly or pieces have not been assembled on the axis

The changes in instructions and material façade did not change the actual level of cognitive automation (still levels 2 and 3) but changed the characteristics of the LoA-solution e.g. the quality of the cognitive support.

After introducing changes in cognitive automation a difference in operator performance was seen in the relation between NPAC and the amount of total assembled parts (Table 3). This ratio shows that the improved instructions and material façade increases the correctly assembled components in proportion to all assembled components. This ratio has an important role when introducing new models or products to operators due to the reduced ramp-up time.

Table 3. NPAC 1, 2 and Total summarized for all participants for each set of experiment as percentage of NPAC.

	NPAC 1	NPAC 2	NPAC Total
Exp. 1	68.79 %	88.15 %	80.60 %
Exp. 2	79.31 %	94.12 %	88.22 %

The results show that the operators in the second experiment set had time to assemble more parts during their limited takt time. This phenomenon is probably a result of the improved cognitive automation, which decreases the non-value adding time, especially motions. The lowered non-value adding time and the increase in the value adding time leads to an improvement of the productivity with 2.1 % (Table 4).

Table 4. Productivity, ratio between output and input.

	Exp. 1	Exp. 2	Change
Value adding time	38.50 s	39.45 s	0.95 s
Non value adding time	36.76 s	36.06 s	-0.70 s
Productivity	51.2 %	52.2 %	2.1 %

The decrease of the non-value adding time by 0.7 seconds and the increase of the value adding time by 0.95 seconds are not equal to each other. The reason for this difference is that the assemblies in the experiments were limited to 20 components in total, and when the operator had assembled all of the 20 parts, the timekeeping discontinued. Therefore, the overall average lead time cannot be equated with the ideally set takt time.

The increase of the amount of correctly assembled parts in the second experimentation set shortens the time it takes to assemble a single part correctly by 0.9 s/NPAC for the new improved instructions and material façade, see Table 5. It is worth noting that the largest difference was observed in the first five assemblies.

Table 5. The time it takes to assemble one part correctly, s/NPAC.

	Cycle 1	Cycle 2	Total
Exp. 1	6.711 s/NPAC	4.682 s/NPAC	5.357 s/NPAC
Exp. 2	5.176 s/NPAC	4.046 s/NPAC	4.451 s/NPAC
Difference	1.535 s/NPAC	0.636 s/NPAC	0.906 s/NPAC

5. DISCUSSION

In a real assembly situation it is difficult to test aspects regarding ramp-up time and how changes affect performance and productivity. Although that this paper describes an experiment situation, the trends and ideas can be used for further testing. Both operator performance and productivity was higher for experiment set 2. The changes made in the experiment set-up were improvements made in instructions and material façade but other aspects could also have affected the situation. For instance the experiment leaders might have become calmer during the second experiment set which could affect the emotion of the participants, and thereby also influencing their performance. However, one could argue that their emotions would not affect participants to that extent. The experiment setting may also have influenced participants in an unwanted way. The constriction of the current laboratory framework restricted possible changes in the design of the workplace layout. However, the limitation serves the purpose of creating resemblances to an industrial reality, where it is not always possible to implement major reconstructions. In addition, the number of participants is quite few for experiment set 2 and therefore the result may be misleading depending on the proportion between expert and novice knowledge in assembling LEGO. Participants had to sign up for the experiments, which may indicate that there exist a prior interest or some previous skill in LEGO assembly. Either way, designing for cognitive conditions in a workplace for the early stages of an implementation phase have an impact on the assembly’s capabilities for its initial production.

The measurement of operator performance was based on the number of parts that were assembled correctly. This assessment could be perceived as harsh since the participants were not made aware of their mistakes, which probably influenced the result in a negative way. However, this assessment could reflect a real assembly system where sometimes the errors are not found until further down on a line. The fact that participants were not allowed to assemble one gearbox before starting could also have influenced the results. They learned the assembly sequence only during the experiment which would often not be the case in a real assembly situation. The results showed that the number of correctly assembled parts, in proportion to the total number of assembled parts, increased by 9.4 % in between the two experimentation sets. This result implies that the improvements in cognitive automation, instructions and material façade, also improved the participants understanding of the tasks. Similar results have been found by Bäckstrand, *et al*. (2008) and Thorvald, *et al*. (2010) where changes in cognitive automation and improved access to instructions respectively, clearly enhanced the quality of tasks.

5.1 Small changes in cognitive automation can result in cost benefits

The results from the experiments show that minor cost-efficient changes that aim to improve cognitive automation may have positive impacts concerning productivity if executed according to literature. Such minor cost-efficient changes do not necessary require changes to the entire workplace layout, but concerns rather small changes to the material façade and assembly instructions in order to better support the workers' cognitive abilities. If the workers are able to achieve high performance during the initial stages of a new production, the production system allows for faster changeovers and reduced interruptions in between productions. This increased flexibility facilitates mass-customization of assembled products. As stated earlier the changes performed did not change the actual level of cognitive automation but the characteristics of the automation (improvements in terms of better quality of the support given to operators).

Since this research suggests that simple cognitive improvements can improve the initial assembly performance, it would be interesting to further study the effects of improving material façades and assembly instructions on the initial assembly performance. Especially concerning whether the two improvement efforts depend on each other to be successful, or if one improvement is more effective than the other. Further, it would also be interesting to study how much improvement that can be achieved and if there are any limit to, or stagnation of, improvements in the initial assembly performance.

5.2 The importance of cognitive automation

The study of system performance should also include aspects of cognitive support and automation usage (Sanchez, 2009). How information was used was captured by using Fasth, *et al*'s (2013) definition of cognitive LoA. These results point towards the importance of the characteristics of the cognitive LoA. That is, not only the cognitive LoA of interest, but the different solutions and characteristics of them within each level. Further studies should be conducted to understand how the characteristics could change within each solution because each automation solution may be perceived differently (Mattsson, *et al*., 2011). As seen in the interviews and previous studies (Thorvald, *et al*., 2010) about what some participants thought was good and others thought were bad. This all depend on how the instructions are presented and how they are perceived. General trends can be found, which can be used to increase knowledge and understanding of cognitive automation support.

6. CONCLUSIONS

To find predictability in a production system it is important to be able to measure and understand how changes in cognitive automation can affect system performance. This study shows that changes in instructions and material façade can improve operator performance and productivity in an experiment setting. The result showed that relatively small changes in the characteristics of cognitive automation could increase operator performance and productivity. Although this was done in an experiment setting, the findings are relevant since potential cost savings could be made by introducing minor changes to existing systems. The importance of studying changes within a LoA-solution is stressed and further studies are needed to support how the changes affect an industrial setting and how different cognitive solutions are perceived within each LoA-solution.

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