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An Empirical Study on Workers' Preferences in Human–Robot Task Assignment in Industrial Assembly Systems

Christina Schmidbauer, Setareh Zafari, Bernd Hader, and Sebastian Schlund

***Abstract*—Collaborative industrial robotic arms (cobots) are integrated industrial assembly systems relieving their human coworkers from monotonous tasks and achieving productivity gains. The question of task allocation arises in the organization of these human–robot interactions. State of the art shows static, compensatory task allocation approaches in current assembly systems and flexible, adaptive task sharing (ATS) approaches in human factors research. The latter should exploit the economic and ergonomic advantages of cobot usage. Previous research results did not provide a clear insight into whether industrial workers prefer static or adaptive task allocation and which tasks workers do prefer to assign to cobots. Therefore, we set up a cobot demonstrator with a realistic industrial assembly use case and did a user study with experienced workers from the shop floor (n = 25). The aim of the user study is to provide a systematic understanding and evaluation of workers' preferences in a practical context of human–robot interaction (HRI) in assembly. Our main findings are that participants preferred the ATS concept to a predetermined task allocation and reported increased satisfaction with the allocation. Results show that participants are more likely to give manual tasks to the cobot in contrast to cognitive tasks. It shows that workers do not entrust all tasks to robots, but like to take over cognitive tasks by themselves. This work contributes to the design of human-centered HRI in industrial assembly systems.**

***Index Terms*—Decision-making, human–robot interaction (HRI), manufacturing, robotics, task assignment, task switching.**

I. Introduction

INDUSTRIAL assembly systems are characterized by a high proportion of manual tasks. The potential for (partial) automation in this area is significant. In particular, this concerns the automotive industry with a share of manual assembly time of 30%–50% and the electronics industry with a share of 40%–70% [1]. In these industries, possibilities such as human–robot interaction (HRI) by deploying cobots for partial automation are being sought that are both cost- and time-efficient, but also do not reduce the flexibility of manual assembly, but at best increase it. However, the relevance of this work stems not only from practice but also from research.

Finding a suitable or even optimal distribution of tasks to allocate to the respective agents in HRI has been an ongoing research challenge over the last decades. The underlying approaches for task allocation have shifted over the years toward a suitable compromise between significant productivity gains and human factors goals such as ergonomics, learnability, and holistic task sets. Human factors approaches claim to design work systems fitting to human characteristics. Therefore, preferences of the workers ought to be considered for the strategic and operational task allocation patterns.

As complementary approaches of task allocation such as flexible, dynamic, or adaptive task sharing (ATS) move into practical applications, recent research puts emphasis on understanding the workers' preferences within human–robot teams [2]. Results suppose that workers tend to prefer giving up tasks and control to the machine agents and prefer to cede control authority to the robot [3]. Furthermore, existing work suggests "that providing workers with a role in the allocation of tasks to their robotic counterparts may not be an effective method of improving worker satisfaction" [3, p. 310]. Somehow these findings conflict with human factors ground truth such as that more holistic, coherent, and autonomous task sets increase learnability and problem-solving skills. Moreover, all prior research on describing and understanding workers' preferences of task allocation in human–robot teams known to the authors has been carried out with "uninvolved" people such as students or campus recruits [3], [4].

In contrast, we focus on the perspective of the actual target group, the assembly workers. This article applies the research setting of HRI within an example assembly use case at an SME manufacturer of electronic devices. Furthermore, the article explores differences and similarities within two settings of task allocation: 1) a static, compensatory setting; and 2) a setting of adaptive task sharing between a human and a cobot. As the actual manufacturing operators are involved within the real factory, the experiment setting affects their "own" workplaces. The main contribution is therefore to enlarge the existing body

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of knowledge for workers' preferences within human–robot task allocation with empirical findings of a real use case experiment.

Our previous, preparatory work for the present contribution includes inter alia empirical studies on the topic human–robot agency and the role of perceived control [5] as well as participatory design in HRI in manufacturing, in particular the development and evaluation of an adaptive task sharing method and software [6], [7], [8], [9]. For this article, we reviewed relevant literature on workers' preferences in human–robot task sharing (cf., Section II) and elaborated on the research gap and five hypotheses (cf., Section III). We implemented an experiment of adaptive task sharing within a real manufacturing environment at an SME (cf., Section IV). After reporting the results of the experiment (cf., Section V), the article concludes with an overall evaluation of the approach and a discussion (cf., Section VI). Finally, Section VII concludes this article.

II. State of the Art

A. Human–Robot Interaction in Industrial Assembly Systems

Industrial assembly work systems are usually characterized by many manual processes, which are executed sequentially. This work is typically very monotonous for human workers. Collaborative industrial robotic arms enable a direct, safe, and ergonomic interaction with their human coworkers in smart factories [10]. Cobots can take over monotonous or unergonomic jobs such as pick & place or quality inspection tasks [11]. They hold a high potential for greater flexibility and efficiency in industrial assembly processes, but they also bring new challenges [6]. In addition to the lack of know-how with the technology and its potential applications [6], safety poses a challenge in HRI in industrial assembly systems. In practice, a cobot application, including the robotic arm, the tools, workpieces, and the robot program must be safety certified in accordance with the ISO TS 15066 [12]. In order not to pose a danger to the human in the event of a possible collision, a cobot can only work relatively slowly in a shared workspace with a human. Additionally, there are new challenges in the field of scheduling to achieve an increase in flexibility and efficiency. Inter alia the identification of suitable tasks and the determination of the best task allocation are critical [13].

B. Approaches to Human–Robot Task Assignment

Task or function assignment can be based on a compensatory, leftover, or complementary approach [14]. In 1951, Paul Fitts compiled a list of advantageous capabilities of (hu-)man and machine. This compensatory approach has been followed for a long time: Tasks or functions that correspond to the advantageous capabilities of humans, e.g., the detection or perception of small amounts of visual or acoustic energy, inductive reasoning, improvisation, and judging should be done by humans and tasks that could be done "better" by machines, e.g., repetitive, routine tasks, multitasking, and deductive reasoning should be automated [15]. Researchers argue that this compensatory approach of task allocation leads to a leftover task allocation where everything is automated that can be automated and only the leftover tasks, such as monitoring, should be done by humans [6]. The negative effects of these static task allocation approaches are often subject to discussion [2], [6], [14], [16], [17].

Researchers from the field of production and human factors propose complementary, more flexible, so-called dynamic or adaptive task assignment approaches to be more favorable for assembly processes and the workers themselves [2], [6], [18]. The main difference between these approaches and the conventional, static task allocation is that there is not one best solution for the task allocation that is made before the assembly process starts, but the assignment decision is adaptable to different decision criteria and can be made also during the process. Decision criteria for different task assignments can be varying requirements of the production process (e.g., small lot sizes required by the customer) or errors of the connected (e.g., the feeding) systems or of the robot itself. The solution can also be adapted according to e.g., the task preferences, physical or cognitive ergonomics of the human workers. Dhungana et al. [19] consider all possible assignments in the task assignment, and show the worker the next possible assignment variants via a so-called `NextOps` function. By means of different key performance indicators such as time/makespan, costs, carbon dioxide equivalent, cognitive or physical ergonomics or worker's preferences the optimal assignment variants can be displayed. Lamon [20] follows a capability-aware role allocation approach, that considers, e.g., the physical ergonomics of the human worker but restricts the decision-making authority of the worker. Gualtieri et al. [21] present an algorithm considering technical, safety, ergonomics, quality, and economics aspects. The final output is either that the task should be finally performed by exclusively the operator or the robot, equally by the operator or robot or by the operator with the help of the robot. A performance quality-based, dynamic scheduling algorithm is proposed by Pupa et al. [22]. This complementary approach is therefore not only promising in terms of the flexibility of a process but enables the focus on the workers well-being in manufacturing. A comprehensive overview of task assignment approaches and algorithms is presented in Schmidbauer [9].

C. Decision-Making Authority in Task Assignment

Fundamental research and basic considerations have so far provided ambivalent conclusions compared to the results of user studies. On the one hand researchers argue that workers should have the decision-making authority in human–robot task assignment. For example, the tendency to separate planning tasks from execution tasks has been criticized as it can lead to deskilled technology users who are not capable or equipped for exception-handling or meaningful decision-making [23]. This view is supported by [24] and [25] which indicate complete tasks enable workers to regulate actions at different mental levels and can increase competencies and motivation of workers. Additionally, Parente et al. [18] highlight the importance of scheduling in the context of Industry 4.0. Mostly the approach is to provide workers with an exact work plan that they should follow and scenarios in which "workers are given more freedom should also be considered, in which they pick their next task from a set of eligible ones and start it at any time during a specific interval" [18]. Recent research on human factors in task

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allocation propose a dynamic "ad hoc" task allocation process, where the human is given the authority to assign tasks to the agents [2]. Tausch et al. [2] developed an allocation decision process model consisting of three steps: 1) allocation criteria definition such as work costs, production time, computational effort, and competence retention; 2) influence on allocation, which refers to the ten levels of automation [26] and the related decision autonomy; 3) allocation communication that describes that the operators need to be provided with information about the cooperation.

On the other hand, user studies concluded that the robot should have the decision-making authority. For example, Gombolay et al. [3] investigated the relationship between decision-making authority, team efficiency, and human worker satisfaction. The results revealed that participants were more satisfied when the robot assigned the tasks on its own or at least remaining tasks that the participant did not want to take over in comparison to when participants had to assign all the task to themselves or the robot and another human assistant. Similarly, Munzur et al. [27] found that participants prefer the semiautonomous robot over the robot that has to be instructed on each action on a collaborative task. This suggests that participants preferred to give the control authority to the robot and were more likely to assign a disproportionate number of tasks to themselves when working with a robot rather than human teammates.

III. Research Gap and Hypotheses

The research gap we want to partially fill with this contribution concerns the empirical investigation regarding the preferences of the workers in industrial assembly systems. In our opinion, previous research does not give a consistent picture of whether workers like to assign tasks themselves or not. Although this is predicted by research, the empirical studies so far have shown a different picture. Furthermore, we want to investigate which tasks workers like to assign to the cobot and which tasks they would like to do themselves. The detailed hypotheses are elaborated below.

First, based on the state of the art, we believe that workers prefer ATS (i.e., having the authority for task allocation decision) rather than merely performing the preassigned tasks (i.e., leftover task allocation), and thus, assume participants evaluate working with a cobot more satisfying when they have authority over task allocation based on research in human factors.

H1: Workers prefer the ATS scenario, where they have the decision-making authority to the leftover scenario, where the (robotic) system assigns the tasks.

We assume that preferring the ATS scenario is affected by some underlying mechanisms. For instance, how the human's perception of control or competence is affected in a human–robot collaboration [28]. While people's attitudes toward robots depend on the amount of control they feel during the human–robot collaboration [5], designing robots that accounts for human values in a comprehensive manner is necessary and well encouraged among guidelines for responsible AI and robotics (e.g., [29]). However, the majority of automation and Industry 4.0 strategies focuses on enhancing machine applicability and industrial productivity that largely considers workers as users rather than collaborators of robots. This leads to an increase of human's dependence on the support provided by the robot assistant that might hinder the sense of control and competence in the workers. As experiencing a sense of freedom and efficacy are highly interrelated [30], we assume that when humans have the authority over task allocation decision, their sense of both control and competence will increase. Thus, the next hypothesis is formulated as follows.

H2: Workers' perception of control and competence are higher in ATS than leftover scenario.

Another factor that can affect the preferences about a task sharing setting is how the cobot is perceived by the humans. While people perceive robots differently than other tools and artefacts [31], [32], the perceived realism of an interaction with a robot can impact how people evaluate the interaction situation. We assume that providing the robot an authority over task allocation improves the human-like perception of the robot and especially the perception of anthropomorphism and intelligence of the robot. We focused only on anthropomorphism and perceived intelligence as these aspects are more affected by the interaction scenario than the actual behavior of the robot [33]. While anthropomorphism has been mostly investigated with regards to social robots, recently the benefits of anthropomorphic robots in industrial context have received attention. For instance, [34] and [35] discussed how anthropomorphism can improve the acceptance of a robot as a cooperative team-partner. Other studies (e.g., [36], [37]) found that anthropomorphizing a robot affects subjective trust and task performance. Moreover, the robot's behavior can provoke people's estimation in terms of its intelligence [38]. Thus, we formulate our next hypothesis as follows.

H3: The perception of anthropomorphism and intelligence of the robot are higher in ATS than leftover scenario.

Furthermore, we expect that the inclusion of the worker in the allocation decision will affect the human workload. Gombolay et al. [4] found that participants would prefer working with a robot that utilized the individuals more frequently as that provided them with a relatively high workload. Previous research has established that human performance is dependent on workload [39]. As increasing the automation level aims at reducing the workload of the human coworker [40], we assume that when humans have the authority over task allocation decision-making processes, their workload will increase.

H4: Workers' perceived workload for the ATS scenario is higher than for the leftover scenario.

One explanation for the mismatch in research on decision-making authority is mentioned by Gombolay and colleagues. They argue that people are more willing to give up their preferences if team fluency improves the process [4]. People also consider their utilization and perceived efficiency in their decision. A closer look at Gombolay's studies reveals that the participants in their studies were recruited exclusively from a local university. The authors also mention this in their limitations and are aware that impressions of robots as colleagues can vary significantly between young adults on a campus and older manufacturing workers.

Klaer and Wibranek [41] did a study on human decisions in HRI concluding with "many participants showed contradictory

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strategies and an inconsistent perception of their decisions". The setup included four different tasks which were characterized in transport and measurement tasks. In four rounds the 12 study participants had to assign the task to the robot or themselves. Interviews revealed that participants who stated that they would prefer to assign tasks with many measurements to the robot, assigned the task with the least measurements to the robot. Participants were also recruited at the university [41].

While recruiting participants from the target populations has been highly suggested in HRI [42], we argue that the analysis of decision-making authority and workers' preferences should not be done by a reference group of students or researchers who may never have worked or will work with a cobot on the shop floor. Therefore, we recruited experienced workers as participants for our user study. Depending on the organization of an assembly process, a worker has a more or less divers task spectrum. This can be distinguished between handling or joining tasks and nonhandling tasks such as checking [1]. The design of a robotic arm including a two-jaw gripper assumes that the robot is suitable for taking over handling tasks. The design of the robot does not suggest that the robot can also perform other tasks even if the setup and the explanation of the use case shows it. Thus, we assume that when participants can assign tasks, they prefer nonhandling tasks to handling tasks.

H5: When participants can assign tasks between a cobot and themselves, they prefer to assign non-handling tasks such as inspecting, confirming, and comparing to themselves.

IV. Methodology

A. Physical Demonstrator

To enable the HRI interaction in assembly, an industrial demonstrator consisting of a cobot, a task sharing user interface, and a use case from an SME manufacturer of electronic devices offering a divers set of tasks was set up. For the cobot, Panda by Franka Emika was chosen, because it offers a high usability [43] and the direct connection to the process-based task sharing software user interface [6], which enabled a fully automated task execution during the experiment. The use case was selected by analyzing several assembly cases within the company's process spectrum. The selection criterion was the highest diversity of tasks to be performed by a worker in an actual workplace. The setup is shown in Fig. 1.

B. User Interface Design for Adaptive Task Sharing

The web-based business process model and notation (BPMN) prototype of [6], [7], and [8], served as a basis and was further developed (see Section System Architecture) to enable ATS. By using BPMN (see Fig. 2) and representing the collaborative human–robot process as a business process, the worker is provided with a very easy-to-use programming environment [7], [8] and can adjust the task allocation before each run if necessary. For this purpose, a variant with three swimlanes was chosen, whereby the top swimlane represents the role of the human, the bottom swimlane the role of the cobot and the middle swimlane contains all those tasks that must be assigned to either the human or the robot. The user can assign the tasks of the swimlane

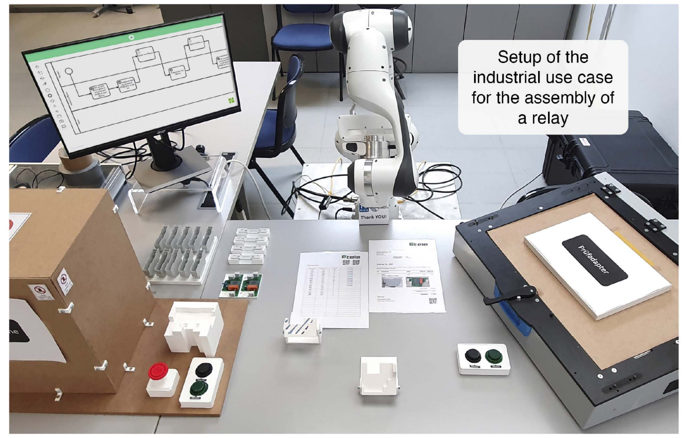

Fig. 1. Cobot demonstrator including user interface for adaptive task sharing and industrial use case.

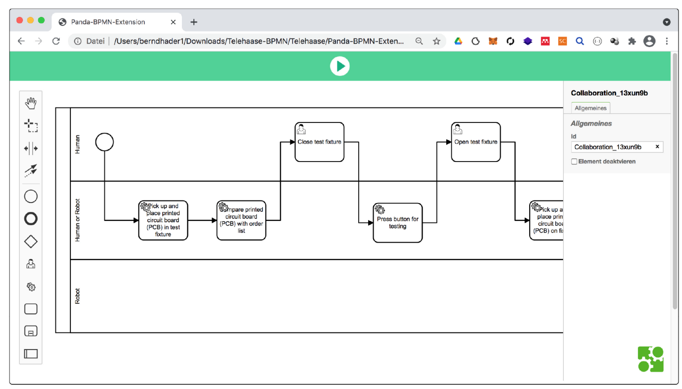

Fig. 2. Screenshot of the ATS user interface including three swimlanes for human, human or robot, and robot tasks.

"Human or Robot," such as the task "Pick up and place printed circuit board (PCB) in test fixture" either to the human (move to the swimlane human) or to the robot (move to the swimlane Robot), via drag and drop. Depending on whether a task has been assigned to the human or the robot, the system either waits for a user confirmation for the corresponding task or controls the cobot when executing the process.

C. System Architecture

The system architecture of [7] and [8] consisting of the four components: Cobot Panda by Franka Emika, External Node.js Task Client, (Camunda) BPMN Engine and web-based user interface, which serves as the basis for modeling and controlling the BPMN-based collaborative human–robot processes, was retained. In [6], ATS was realized by creating different work-sharing variants of a process; the user can choose the preferred variant for each run. On the one hand, this approach makes it possible to switch quickly between different variants, but on the other hand it also restricts the user greatly in the choice of task assignment. Considering the assembly process used, which consists of 18 tasks, 13 of them can be performed by both human and robot, there are 8192 different possibilities for the division of labor. To enable the user to create her or his preferred

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variant very easily, it was necessary to adapt the web-based user interface of [7] and [8]. This was realized through the use of a third swimlane "Human or Robot" (see Fig. 2). The creation of pools with three or more swimlanes is provided by default by the used web-based BPMN Modeler from BPMN.iO [44]. The main functionality that needed to be integrated was the conversion of tasks (service/user task) when moving to another swimlane. This was implemented entirely in the user interface using JavaScript (JS). All other components of the system architecture of [7] and [8], thus, remained unchanged and could be reused without adaption. The developed prototype is open source and available online for download [45].

D. Use Case

The use case was analyzed regarding its tasks to be accomplished. In total, 18 tasks were identified and analyzed based on the ATS task analysis procedure developed by [9]. First, the tasks were classified in the functions handling, checking, joining, and special in reference to [1].

This classification was further used for the analysis of the results. For the task preassignment, it was analyzed step by step whether the task could be done by a robot (feasibility), whether safety-critical situations could occur during the task and which effects the task has on the ergonomics of the employee [10]. Ergonomic considerations were only taken into account to the extent that the individual is able to complete the task from a seated position, or if the design of the workstation would cause them to stand up and reach over, which would not be ergonomic. An economic consideration of the tasks was conducted, but did not factor into the initial task allocation, as it was not intended to influence the elicitation of workers' preferences.

E. Study Design

To understand how the authority over task assignment affects collaboration and worker's perception within a human–robot team, we compared the two approaches of task assignment with a cobot: ATS and leftover setting. To mitigate the effects of intersubject variability for preferences on task assignment condition, we conducted a within-subject experiment in which all participants experienced both conditions once. The degree of automation (or authority) over task assignment was manipulated at two levels: ATS as condition A and leftover as condition B. While in condition A, the participants were asked to decide which tasks to assign to the cobot and which to perform themselves, participants in condition B were instructed which tasks the robot can perform. To counterbalance the possible learning effects over the different trials, participants were randomly divided into two groups: 1) 12 participants first underwent condition A and then condition B; while 2) 13 participants started with condition B and then A.

F. Procedure

Upon arrival, participants were given an overall description of the study and watched a safety instruction video. Following informed consent, participants were instructed to complete a preliminary survey in which they were asked to rank all 18 tasks from least to most favorite. Before starting with the experiment, participants received training on the elements of the interface and task. Next, the two conditions were presented to the participants in a randomized order. After each condition, participants were asked to assess their perceived control, competence, workload, and humanness perceptions of the robot. After being exposed to both conditions, participants answered a posttest survey with demographic and open-ended questions, inviting them to describe their experiences and preference of the collaboration, as well as the criteria for task assignment. At the end, they were debriefed and received a thank-you gift. The survey instruments were provided in both German and English upon request.

TABLE I
SUBJECTIVE MEASURES FOR SCENARIO EVALUATION

Likert scale questions
1. I am satisfied with how the tasks were allocated to me and robot. 2. I am satisfied with how the tasks were executed. 3. I am satisfied with the result of working with the robot. 4. The robot and I collaborated well together. 5. I would work with the robot the next time the tasks were to be completed.
Open-response questions
6. Which of the two scenarios did you prefer and why? 7. If you were going to add a robotic assistant to a manufacturing team, to whom would you give the job of task allocation and why?

G. Participants

A total of 25 participants (12 female, 12 male, and 1 unreported), employed at Tele Haase Steuergeräte Ges.m.b.H., an Austrian manufacturer of electronic devices, were recruited voluntarily through the company. Participants were between 18–59 years old ($M = 37.6$, $SD = 11.37$) with average tenure of six years. The majority of the participants were from the production (88%) and the rest from the development department (12%).

H. Measures

Subjective measures assess the worker's perceptions and preference [46]. For scenario evaluation, we used 5-point Likert scale (1 = strongly disagree, 5 = strongly agree) statements and two open-ended questions adapted from [2] and [4] as shown in Table I.

Treatment variables: Workload was measured via the NASA-TLX [47]. Perception of control was measured with four items adapted from [48]. A sample item is "I had control over the task performance." Items were rated on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree) and showed an internal consistency of a Cronbach's Alpha =. 90 and. 73 (we report the alpha twice as we measured the variables after each scenario). Perception of competence was measured with 6 items adapted from [49]. A sample item is "I felt that I was able to complete the task." Items were rated on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree) and showed an internal consistency of a Cronbach's Alpha =. 83 and. 85. Participants' perception of intelligence and anthropomorphism of the cobot was measured by a six-item semantic differential scale adapted from [50]. The

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TABLE II
FAILURES AND MISTAKES DURING EXPERIMENT

Caused by system	Caused by participant	Corrected by
1-leftover 1-ATS 3-leftover 5-ATS	17-ATS	Participant
3-leftover 3-ATS 5-leftover 8-leftover	2-ATS 8-ATS 13-ATS 14-ATS 25-leftover	Experimenter
4-leftover	-	Cobot
13-leftover	18-leftover 18-ATS	Nobody, intervention was not necessary

Number indicates participant (1-25) e.g., 1-leftover means that there was a failure when the participant no. 1 was in the leftover scenario

TABLE III
MEAN RANK FOR FIVE SCENARIO EVALUATION QUESTIONS PER CONDITION

Question		N	Mean Rank	p
1.	ATS $<$ Leftover	2	3.5	.03
	ATS $>$ Leftover	8	6	
	ATS $=$ Leftover	15		
2.	ATS $<$ Leftover	5	4.90	.80
	ATS $>$ Leftover	4	5.13	
	ATS $=$ Leftover	16		
3.	ATS $<$ Leftover	6	5.75	.46
	ATS $>$ Leftover	4	5.13	
	ATS $=$ Leftover	15		
4.	ATS $<$ Leftover	8	6.94	.04
	ATS $>$ Leftover	3	3.50	
	ATS $=$ Leftover	14		
5.	ATS $<$ Leftover	4	5.13	.80
	ATS $>$ Leftover	5	4.90	
	ATS $=$ Leftover	16		

Cronbach's Alpha for perceived intelligence were. 71 and. 73. The Cronbach's Alpha for anthropomorphism were. 85 and. 79.

Background variables: Perceived usability of the system was measured by ten items from the System Usability Scale [51]. The Cronbach's Alpha was. 88. Participants' age, gender, tenure, and experience in production/assembly were asked additionally.

V. RESULTS

The data was analyzed using IBM SPSS version 26 and Microsoft Excel. Differences between groups of normally distributed populations were assessed by analysis of variance (ANOVA) and differences between populations with a nonparametric distribution were assessed by the Wilcoxon signed rank test.

A. *Unexpected Events During Experiment*

Some minor failures and mistakes happened during the experiment, caused either by the cobot (system) or the participant. As shown in Table II, the frequency of failures is equal between the two conditions (nine times in ATS and nine times in leftover). While participants caused more mistakes in ATS than leftover conditions, the system caused more failures in leftover than ATS condition. In total, no mistakes completely interrupted the process; in most cases, only minimal corrections were necessary. One example of a failure is that the assembled case was slightly skewed in the labeler, so in a real process there would be an error. Another exemplary mistake by the participant was that they put the case on the wrong fixture. Some of these failures and mistakes were corrected by the participant, some by the experiment leader and some by the cobot. Moreover, not all of them were noticed by the participants because they did not know the ideal state of the process.

B. *Scenario Preferences*

Table III shows an overview of responses to the five subjective questions for scenario evaluation from Table I. While a significant difference was observed in the satisfaction with allocation process ($Z = -2.15$, $p <. 05$), participants did not rate differently the execution satisfaction ($Z = -.25$, $p =. 80$) or result satisfaction ($Z = -.74$, $p =. 46$). However, participants reported a better collaboration with the robot in leftover condition than ATS ($Z = -2.05$, $p <. 05$).

With regards to the two open questions, cf., Table I, there was a significant difference in the answers to "Which of the two scenarios did you prefer?" ($\chi^2(2) = 4.48$, $p <. 05$), such that the higher number of participants (18/25) preferred the ATS rather than leftover condition. Fisher's Exact Test revealed that the preferences are independent of whether they work in assembly or not ($p =. 53$). Similarly, in the responses to the question "If you were going to add a robotic assistant to your manufacturing team, to whom would you give the job of task allocation?", the majority of participants chose the person involved in production ($\chi^2(2) = 8$, $p <. 05$). A reason mentioned by four participants for not preferring a robot to do the task allocation was the lack of experience in production. For instance, one participant commented: "We have performed these tasks for a relative long time and are aware of the requirements and challenges of each component." Other concerns were expressed about increased complications, having a more secure feeling over the whole process, and being actively involved in the task completion. Together these findings support our Hypothesis 1 stating that workers prefer ATS to leftover scenario.

We observed a statistically significant difference for perceived control, $F(1, 24) = 27.76$, $p <.001$, as well as perceived competence between the experimental conditions, $Z = -2.20$, $p <.05$. This supports Hypothesis 2.

Hypothesis 3 stated that the perception of anthropomorphism and intelligence of the robot are higher in ATS than leftover scenario. Results show that participants anthropomorphized the cobot more in ATS than leftover condition, $F(1, 24) = 5.19$, $p <.05$. However, there was no difference for perception of intelligence in the cobot between the two conditions, $Z = -.22$, $p =.82$. Thus, Hypothesis 3 is not fully supported.

Recall that Hypothesis 4 predicted that workload for ATS is higher than leftover condition. There was no significant difference on the total NASA-TLX score, $Z = -.21$, $p =. 84$. However, result on each NASA-TLX subscales (i.e., mental demand, physical demand, temporal demand, performance, effort, and

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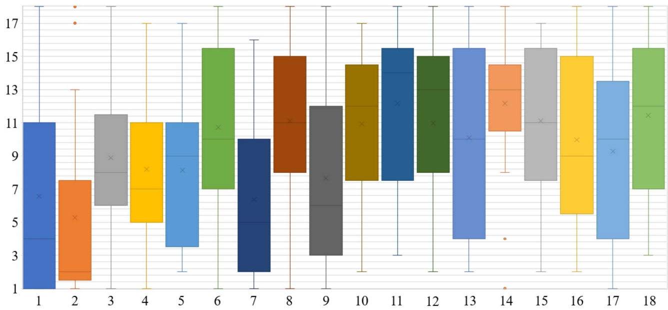

Fig. 3. Ranking of tasks: horizontal axis shows tasks 1–18, vertical axis shows ranking including median (line) and average (cross), 1: most preferably assign to human, 18: least preferably assign to human (n = 25).

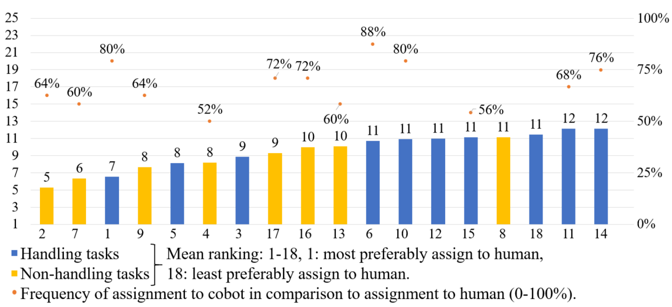

Fig. 4. Comparison between ranking and assignment of tasks to the cobot. Tasks 3, 5, 8, 12, 18 were preassigned.

frustration) showed a statistically significant difference only for physical demand, $Z = -2.33$, $p < .05$, stating that participants rated a higher physical workload in ATS than leftover condition. This was expected since leftover condition requires participants to perform only four tasks.

C. Task Preferences

1) Ranking of Tasks Before Interaction: As mentioned in section F "Procedure," participants ranked the tasks from most favorite to least favorite before they were exposed to any condition and interacted with the cobot. A Friedman test indicated that tasks were rated differently ($X^2(17) = 64.16$, $p < .001$). The Kendall's W is. 15 which indicates a small effect size as well as poor agreement between participants on the preferable ordering of the task. However, the most favorite task was "Compare PCB with order list" and the least favorite tasks were "Pick up and place cover on case" and "Pick up and place component for labeling." Fig. 3 shows the ranking of all 18 tasks. The tasks were sorted to the mean ranking, shown in Fig. 4. The descriptions of the tasks are shown in Table IV.

2) Assignment of Tasks in ATS Scenario: For Hypothesis 5, we focused on ATS condition. In the leftover scenario, the assignment of tasks was given. Most tasks were assigned to the cobot, only four tasks were assigned to the human, because of the reasons mentioned in section D "Use Case." In the ATS scenario the participants were asked to assign the shared tasks to either themselves or the cobot. This assignment was compared with the results from the ranking, shown in Fig. 4. To be able to compare the two metrics, the ranking was divided into three categories Ã¡ six tasks: six human and six robot favorable, and the six between were marked as indifferent. The assignment was ordered too. The six tasks that were assigned the most to the human and robot were identified. One task in the middle was marked as indifferent. Five tasks were preassigned to the human or robot (i.e., task 3, 5, 8, 12, and 18).

There were seven checking tasks, of which four tasks were ranked and assigned human favorable. Two were ranked indifferently and the assignment was for one human and for the others cobot favorable. One checking task ("press button for labeling") was ranked cobot favorable, but the assignment was then human favorable. One task ("updating the order list") was categorized as special and was ranked indifferently and assigned cobot favorable.

There were two joining tasks. One was ranked indifferently and mostly assigned to the cobot, the other one was ranked cobot favorable, and the assignment was predefined.

There were eight handling tasks: Two were ranked human favorable but the assignment was cobot favorable or predefined; two were ranked indifferently, and assigned predefined or cobot favorable; four were ranked cobot favorable and either assigned predefined (2) or indifferently (1) or to the cobot (1). Some inconsistencies were identified, e.g., the first task "pick up and place PCB in test fixture" was ranked human favorable, but participants mostly assigned the task to the cobot. It seems that most participants wanted to delegate the first task in the process to the robot. This could be due to the uncertainty regarding the process. Another explanation could be that this may have occurred due to the approach to ranking. The participants ranked the first task higher, which means human favorable and the last task lower, which means robot favorable (the last task was ranked low). Detailed comparisons of the ranking and assignment of each task are presented in Table IV.

3) Replicating the Leftover Scenario: Four participants (5, 13, 22, 25) assigned all possible tasks to the cobot, exactly like in the leftover scenario. Three of them (5, 13, 25) started with the leftover scenario, so they replicated the already seen scenario. Reasons why participant 5, 13, and 25 replicated the scenario, could be that they wanted to check if the happened failures and mistakes could be eliminated. One (22) started with the ATS and eventually wanted to see what the cobot is capable of doing and therefore assigned all of the tasks to the cobot.

VI. Discussion

A. Scenario Preferences

The aim of this study was to provide a systematic understanding and evaluation of workers' preferences in a practical context of HRI in assembly. To investigate the differences between the two task assignment settings, we focused on the assessment of the task assignment process that underpin workers' preferences.

We found that participants generally preferred the ATS rather than leftover condition. Our finding is contrary to that of [3] and [27] indicating people prefer ceding complete decision-making authority to the robot. This discrepancy could be attributed to lack of experience in assembly and to the fact that the participants in our study have a real interest in the design of their own workplaces. While students or people outside of manufacturing

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can only abstractly imagine an assembly workplace and cannot relate the situation so much to themselves personally.

The results of this study indicate that having an authority over allocation decision improves participants' satisfaction with the allocation process, but not necessarily with the task execution and result. This finding is contrary to previous studies which have suggested that if individuals are satisfied with decision process, they will also be satisfied with the outcome after execution [2]. This inconsistency may be due to external factors experienced during the interaction. For instance, possible sources of error/failure could have affected the evaluation of task execution and result. Errors caused by the participants during the interaction that required an intervention occurred more often in ATS than leftover scenario (5:1), which may lead to disappointment with the outcome of collaboration. Another possible explanation for low task execution and resulting satisfaction is that the speed of robot's movement was perceived too slow by most of the participants. To ensure the safety of the participants during the experiment, the cobot was not programmed to move as fast as possible. With regards to speed feedback, we explained to them that while the robot could run a little faster, there are limits to how fast it can run due to the safety aspects of a cobot [12]. Hence, it could conceivably be hypothesized that in the long run, when the workers are able to adjust the speed, a positive affect on task execution and result is achievable. This is an important issue for future research in human–robot collaboration.

Results from our experiments show how perception of control and competence, human-likeness of robot and workload change as the consequences of varying the level of human intervention during the decision-making process. Consistent with [52], we found that the participants' perception of control and competence are richer when they have authority over allocation decisions. This finding has important implications for integrating cobots in the workforce, as feeling competent and autonomous are important for maintaining the intrinsic motivation and feeling effective at work [30]. Moreover, participants perceived the cobot in ATS as more human-like than leftover condition. While previous studies showed that human estimations of the robot's capability and intention are important factors in delegating tasks to the robot [53], our findings show that the collaboration in a static setting affects the perception of anthropomorphism but not the intelligence of the robot. This suggests that increasing the automation level of the robot by assigning the decision-authority for allocation decision may not lead to an increase in the robot's perception of intelligence. Finally, while the physical workload increased in ATS scenario, participants cognitive workload has not been rated differently, suggesting that the decision-authority did not increase participant workload during collaboration. Consistent with the literature [24], [52], these results suggest that allowing the individuals to make the decision for allocating the work between themselves and a cobot can be used as a tool to maintain an active role as well as high motivation at work.

B. Task Preferences

To establish a common model to breakdown collaborative work to be carried out by humans or cobots, we analyzed the allocated tasks in ATS condition. In summary, tasks that are characteristic of checking (cognitive) tasks such as comparing, confirming, or inspecting were more likely to be assigned to the human and handling or joining (manual) tasks to the cobot. There are several possible explanations for this result. For instance, lack of experience in working with a cobot could prevent taking the most out of this technology [3].

These relationships may partly be explained by improper mental models of the capabilities of the robot [38], suggesting that the design of the robot arm create the expectations in humans that it is only capable of these handling and joining tasks. A common mentioned criteria amongst participants for choosing the robot or human to do a task was the competence of agents. This finding broadly supports the work of other studies focusing on anthropomorphic robots indicating that people are generally willing to delegate tasks to robots and delegate arithmetic tasks significantly more often to a robot than social tasks [54]. The study by Wiese et al. [54] showed that participants delegate tasks to a robot, when the robot is perceived to be capable of executing the task. Even if the participants are told beforehand that the robot could perform all the tasks, they still decide subjectively, possibly on the basis of implicit biases concerning the capability of the robot. A similar pattern was exposed in our study. Participants were told that the cobot is capable of doing all these tasks and this was also proven in the leftover scenario. However, after the assignment, participants mostly mentioned the perceived competence of the agents as decision criteria.

C. Limitations

The generalization of the results is subject to certain limitations. For instance, all participants interacted with such a cobot for the first time resulting in a high novelty effect. Although the participants saw a (safety instruction) video of the cobot beforehand, it can be assumed that the robot's abilities and action possibilities were not completely clear to all and therefore participants wanted to test the performance of the robot on different types of tasks.

Furthermore, the sample was from one SME manufacturer which might be considered as not representative for the assembly workers in all production settings. Future studies on the current topic are therefore recommended. Another limitation refers to the process execution instruction given to the participants. This lacked reasonable process quality goals, e.g., task performance and execution time. This may have caused to much freedom to the participants to do whatever they wanted without assessing the task performance or execution time and could have affected the level of satisfaction with the system. Last but not least, the study measured mostly subjective measurements to capture the preferences of workers while collaborating with a cobot. A further study could assess the objective measurements such as anxiety, stress level and duration of task completion in order to provide additional insight into the mechanistic influences on different types of task assignments.

Notwithstanding these limitations, this study is a first approach to the topic in a practical setting. A natural progression of this work is to analyze whether time pressure can affect the task preferences. Moreover, the results of the assignment showed a slight tendency that people take over tasks that are spatially

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TABLE IV
COMPARISON RANKING AND ASSIGNMENT OF TASKS

No.	Task	Function	Comparison R & A	Comment
1	Pick up & place PCB in test fixture	Handling	R was H favorable, A was C favorable	Most participants delegated the first task in the process to the C. This could be due to the uncertainty regarding the process.
2	Compare PCB with order list	Checking	R and A were H favorable	Checking tasks are perceived more favorable for H.
3	Close test fixture	Handling	R was indifferent, A was predefined	
4	Press button for testing	Checking	R and A were H favorable	Checking tasks are perceived more favorable for H.
5	Open test fixture	Handling	R was H favorable, A was predefined	
6	Pick up & place PCB on fixture	Handling	R was indifferent, A was C favorable	However the R was indifferent, handling tasks are perceived more favorable for C.
7	Compare individual order with order list	Checking	R and A were H favorable	Checking tasks are perceived more favorable for H.
8	Pick up & place case on fixture	Handling	R was C favorable, A was predefined	Handling tasks are perceived more favorable for C.
9	Visual inspection of case	Checking	R and A were H favorable	Checking tasks are perceived more favorable for H.
10	Pick up & place PCB in case	Joining	R was indifferent, A was C favorable	However the R was indifferent, handling tasks are perceived more favorable for C.
11	Pick up & place cover on case	Handling	R was C favorable, A was indifferent	Handling tasks are perceived more favorable for C.
12	Tighten/fix the cover	Joining	R was C favorable, A was predefined	Joining tasks are perceived more favorable for C.
13	Visual inspection of the component	Checking	R was indifferent, A was H favorable	However the R was indifferent, checking tasks are perceived more favorable for H.
14	Pick up & place component for labeling	Handling	R and A were C favorable	Handling tasks are perceived more favorable for C.
15	Press button for labeling	Checking	R was C favorable, A was H favorable	
16	Visual inspection of the component	Checking	R was indifferent, A was C favorable	Tasks at the end of the process were more favorably assigned to the C.
17	Updating the order list	Special	R was indifferent, A was C favorable	Tasks at the end of the process were more favorably assigned to the C.
18	Placing the product for transport	Handling	R was C favorable, A was predefined	Handling tasks are perceived more favorable for C.

R = Ranking, A = Assignment, H = Human, C = Cobot

closer to them and tasks that were spatially closer to the robot were assigned to the robot. This result was not significant and could be tested in further studies.

VII. CONCLUSION

The aim of the presented research was to examine workers' preferences in a human–robot collaborative assembly use case. In this article, we presented the results of a user study with 25 participants, working at an SME manufacturer of electronic devices. This study has shown that the majority prefers a flexible work assignment enabled through adaptive task sharing to a static one, where the tasks are preassigned by the (robotic) system. We found that having an authority over allocation decision improves participants' satisfaction with task allocation and their perception of control and competence. The investigation of task allocation has shown that participants preferred to assign cognitive tasks, such as checking, to themselves and manual tasks, such as handling, to the cobot. Results of the assignment indicate that workers like to participate directly in the assembly process, while only a small amount of people (16%) decided to assign all tasks that could be automated to the robot. This study lays the groundwork for future research into preferences of workers in robot task assignment by focusing on the reaction of individuals while working with a cobot. The introduction of cobot technology can disrupt traditional working processes and norms and the implication of the workforce's preferences can directly influence adoption as well as success of HRI long-term.

As part of future research, a review and further exploration of workers' preferences could be implemented through the ATS approach. A longitudinal study, in which workers are allowed to adaptively share tasks, would provide insight into whether preferences stay over time or change. Regular interviews with the workers could provide context. Additionally, the long-term effects on productivity, process flexibility, and human factors could be evaluated.

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