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The Impacts of Human-Cobot Collaboration on Perceived Cognitive Load and Usability during an Industrial Task: An Exploratory Experiment.

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1 **The impacts of human-cobot collaboration on perceived**
2 **cognitive load and usability during an industrial task: an**
3 **exploratory experiment**

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20 **Occupational applications**

21 Since cobots (collaborative robots) are increasingly being introduced in
22 industrial environments, being aware of their potential positive and negative
23 impacts on human collaborators is essential. This study guides occupational health
24 workers by identifying the potential gains (reduced perceived time demand,
25 number of gestures and number of errors) and concerns (the cobot takes a long
26 time to perceive its environment, which leads to an increased completion time)
27 associated with working with cobots. In our study, the collaboration between
28 human and cobot during an assembly task did not negatively impact perceived
29 cognitive load, increased completion time (but decreased perceived time demand),
30 and decreased the number of gestures performed by participants and the number of
31 errors made. Thus, performing the task in collaboration with a cobot improved the
32 user's experience and performance, except for completion time, which increased.
33 This study opens up avenues to investigate how to improve cobots to ensure the
34 usability of the human-machine system at work.

35

36 **Technical Abstract**

37 Background: Industry 4.0 implements smart technologies to increase productivity
38 and to decrease the associated risks. Using cobots is considered by industry as a
39 potential means to reduce physical constraints and improve performance without
40 having to replace the human factor. Research has yet to prove these benefits on
41 humans.

42 Purpose: The goal of this study was to determine if working with a cobot improved
43 perceived cognitive load of an operator and the usability of the system.

44 Methods: Participants replicated three construction models using Duplos.
45 Approximately half of our participants (n=32) accomplished the task alone and
46 the other half accomplished the same task with a cobot (n=22). We then used the
47 NASA TLX to measure workload and, through a sub-dimension, perceived
48 cognitive load. Completion time (for each model), number of errors (placing and
49 replacing a piece), and the number of gestures (movements of the upper limbs)
50 were also measured.

51 Results: Collaboration with a cobot led to significantly fewer gestures (51 vs. 74),
52 fewer errors (2 vs. 8), and reduced perceived time demand, but increased
53 completion time (136 vs. 55 s). Perceived cognitive load was not impacted by the
54 cobot (36 vs. 37).

55 Conclusion: We conclude that collaboration with a cobot adapting to human
56 variability is possible, and that it could lead to better performance and could
57 improve certain dimensions of system usability.

58

59 **Keywords:** collaborative robot; UX; Industry 4.0; human-machine interface;
60 efficiency; cognitive load; usability.

61

62 **1. Introduction**

63 Collaborative robots (cobots) are increasingly popular in industrial
64 workplaces because they are perceived as a means to enhance performance,
65 particularly in future industrial workflows that routinely integrate new technologies
66 into production chains (INRS, 2018). The term “cobot”, created by Colgate &
67 collaborators (1996), refers to “a robotic device which manipulates objects in
68 collaboration with a human operator” (p. 1). The development of artificial
69 intelligence offers cobots adaptive qualities: adaptations to production dynamics, to
70 technical variabilities (Swamidass, 2000), and to the operator. Yet the artificial
71 algorithms remain at an experimental level and need to be improved and evaluated
72 before implanting cobots with adaptive capabilities into industry. Human-cobot
73 interactions can take on several forms. In this report, we will only discuss direct
74 collaboration (working simultaneously on a task). To accept this collaboration, it is
75 essential to study the impacts of the introduction of collaborative robots on
76 operators before implementation (Kildal et al., 2018).

77 In many studies, the human-robot interaction experience is referred to as
78 “user experience” or “UX” (Hassenzahl, 2008). This experience can be studied
79 through the concept of usability (Bevan, 2009; Davis, 1989; Dubey & Rana, 2010;
80 INRS, 2018; Nielsen, 1994). Indeed, studying a system’s usability is a way of
81 guiding its design (Chaniaud et al., 2020). According to ISO 9241-11, a standard
82 reference defining human-machine interaction (Bevan et al., 2015), usability is
83 defined as “the extent to which a product can be used by specified users to
84 accomplish specific goals with effectiveness, efficiency and satisfaction in a

85 particular context of use” (ISO, 2018). Effectiveness is the accuracy and degree of
86 completion with which users will accomplish set goals (ISO, 2018) and is
87 measured through the quality of the results, the quantity produced, and the
88 percentage of goals accomplished. In this study, we use the number of errors to
89 measure effectiveness. Indeed, this gives a behavioral measure of cognitive load,
90 since Verhulst (2018) defined cognitive load as the amount of cognitive resources
91 expended at a given time on a task.

92 Moreover, there are various measures for measuring cognitive load:
93 subjective and objective (Cain, 2007b; Kramer, 1990). Objective measures can be
94 obtained by studying individual performance on the task (Paas et al., 2003): if a
95 task is too onerous in cognitive resources, the individual performing this task will
96 no longer be able to provide all the necessary resources and consequently their
97 performance will decrease. Efficiency is the degree to which the user performs the
98 task easily with a minimum of resources (ISO, 2018). We use task completion time
99 and the number of gestures to measure efficiency in our study. Finally, satisfaction
100 is defined as “the extent to which the user's physical, cognitive and emotional
101 responses resulting from using a system meets the user's needs and expectations”
102 (ISO, 2018). The perceived cognitive load, an indicator of the user’s cognitive
103 response as a result of using a system, is used as a measure of the satisfaction
104 dimension of usability. Subjective measures of cognitive load can be obtained
105 through questionnaires where participants are asked questions directly. In this
106 study, we use the NASA-TLX (Hart & Staveland, 1988), which measures
107 workload as a whole but also more specifically cognitive load, physical load,
108 temporal demands frustration, effort, and performance (Hart, 2006). Also, we
109 consider that usability and cognitive load are two theoretical fields that could be
110 linked to measure UX as a whole.

111 We hypothesized that a human-robot collaboration will reduce the cognitive load

112 required to perform a task, despite the potential increase of cognitive load from
113 introducing collaboration into the task (Kildal et al., 2019). We assumed that
114 collaboration will allow better performance: increased effectiveness, efficiency,
115 and satisfaction. Our operational hypotheses were:

- 116 - H1 = perceived cognitive load will be lower for an assembly task in a condition
117 of collaboration with the cobot than in a control condition.
- 118 - H2 = completion time will be lower for an assembly task in a condition of
119 collaboration with the cobot than in a control condition.
- 120 - H3 = the number of errors will be lower for an assembly task in a condition of
121 collaboration with the cobot than in a control condition.
- 122 - H4 = the number of gestures will be lower for an assembly task in a condition
123 of collaboration with the cobot than in a control condition.

124

125 **2. Material and methods**

126 54 participants (mean age = 21.4 years, SD = 3.9; 42 women and 12 men)
127 consented to participate in the experiment at the University of Grenoble-Alpes.
128 They did not receive any financial compensation for their participation; however,
129 psychology students could request extra credits on a set of classes. They had no
130 vision impairment (colorblindness, etc.). Our study took place during the Covid
131 semi-lockdown and we obtained the approval of the director of the inter-university
132 laboratory of psychology of Grenoble to run the experiment with human
133 participants. Participants were given explanations on the experiment itself and how
134 their data will be handled. After this introduction, they were given a consent form
135 to sign in order to continue the study. We developed a two-condition between-
136 subject design. Participants were randomly assigned to a group. In the control

137 condition, 32 participants performed the task alone, whereas in the experimental
138 condition, 22 participants performed the task in collaboration with a cobot (Figure
139 1). The cobot used for the task is a YuMi (short for You and Me) created by ABB
140 Robotics enterprise (ASEA Brown Boveri). It was used for three reasons: first, it is
141 an industrial cobot that is already implemented in many industrial factories,
142 second, it is the most “collaborative” robot currently existing, and third, it has high
143 safety included in the design (rubber padded joints, curved angles, etc.) to work
144 "safely" in close proximity with human operators. Recruitment for the control
145 condition took place in April because the cobot was not ready yet. Recruitment for
146 the experimental condition took place in May, during the covid restriction. The two
147 groups were uneven for this reason.

148



149

150 Figure 1. The YuMi robot (ABB) used in the experimental condition.

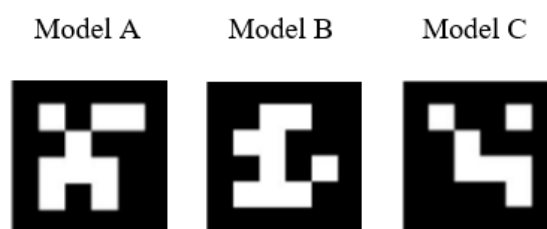
151

152 The cobot was programmed on different levels through a modular robotic
153 architecture. First, the vision module perceives the environment and the presence
154 of the participant's hand during the perception phase to ensure a true description of
155 the environment that is not occluded by the participant's hand. This stage was
156 performed using Python programming language, and the OpenCV computer vision
157 library. Second, the environment description obtained from the perception module
158 is used to infer the progress of the collaborative task carried out by the robot and

159 the participant. This information is used to drive a cognitive conceptual model,
160 which in turn makes use of Automated Planning techniques to generate adaptive
161 intelligent behavior that corresponds to the variability of the assembly task. The
162 intelligent behavior is a plan: a sequence of actions that composes the pick/place
163 task (opening the gripper, moving the robot arm from one place to another, closing
164 the gripper, etc.). Third, the sequence of actions generated to accommodate task
165 variability in an intelligent manner is executed on YuMi using the low-level
166 assembly language RAPID provided by ABB (the manufacturer of the robot).
167 Finally, the plan (intelligent behavior composed of a sequence of actions) and the
168 robot motion are projected on a screen through Graphical User Interface (GUI) to
169 explain the intelligent behavior to the participant by making them aware of what
170 will happen next.

171 Our aim was to develop a type of task that could be performed both in
172 collaboration with a cobot or alone, and that would support study of cognitive load
173 while considering the technical constraints of the cobot. We chose to simulate a
174 typical task in the industrial environment: an assembly of components. In our
175 exploratory study, the task was carried out using Duplos (Lego). Each participant
176 was required to replicate three models (Figure 2).

177



178

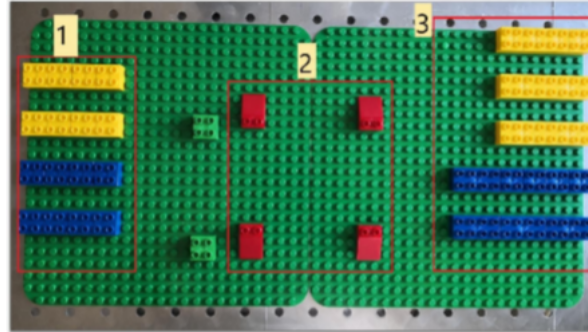
179 Figure 2. The three models that participants were required to replicate.

180

181 The order of presentation of the models was randomized. Each participant had a
182 stock of Duplos located on their left (Area 1 in Figure 3). They had to replicate the
183 model in the “construction zone” (Area 2 in Figure 3). In the experimental

184 condition, the cobot's stock was placed on the participant's right (Area 3 in Figure
185 3).

186



187

188 Figure 3. Location of the construction zone (2), the participant's stock (1), and the
189 cobot's stock (3).

190

191 In the experimental condition, the cobot collaborated with the human by placing
192 pieces on the construction area at the same time as the participant, by indicating if
193 an error had been made using the communication interface and by providing
194 additional stock to the participant (between the green Duplos left of Area 2). The
195 cobot alternated between actions (Table 1) and perception phases (during which it
196 would stop and analyze the Duplos placement). Its instructions were the same as
197 the human's: it had to complete the model. During most of the experiment, the
198 pace was set by the participant and the cobot had to adapt. However, due to
199 technical constraints, the participants could not act when the cobot was in
200 perception phase. They had to wait and regain control of the pace once the
201 perception phase ended.

202

203 Table 1. An example of a human-machine process chart in the experimental
204 condition.

Time (in
seconds)

Participant

Cobot

0-5	Looks at the model	Warns the participant of its next move on its screen
5-10	Looks at the screen to learn where the cobot will pick its piece	Initiates the movement to pick a piece
10-15	Picks a piece	Picks a piece
15-20	Places a piece and looks at the model	Initiates the movement to place the piece
20-25	Picks and places two other pieces	Places a piece
25-30	Picks and places another piece	Warns the participant of its perception phase on its screen
30-40	Waits and looks at the screen	Takes a picture of the construction
40-45	Looks at the model and the screen	Warns the participant of its next move on its screen
45-50	Picks and places another piece	Initiates the movement to pick a piece to make up for a mistake made by the participant
50-55	Picks and places two other pieces	Picks a piece
55-60	Looks at the model	Initiates the movement to place the piece in the correct space
60-65	Picks and places the last piece	Places the piece in the correct space
65-70	Looks at the model and the construction	Warns the participant of its perception phase on its screen
70-75	Waits and looks at the screen	Takes a picture of the construction
75-80	Waits and looks at the screen and the model	Warns the participant of the success of the construction
80-85	Looks at the experimenter for instructions	Goes into standby mode

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In the control condition, participants had a three-minute training session with a demonstration on how to complete a model. The experiment took place in a ventilated room with adequate lighting. In the experimental condition, participants had five minutes of training on how to complete a model and how to interact with

210 the cobot. No participant demonstrated substantial mental or physical fatigue. They
211 were given special instructions to consult the screen of the cobot to know where it
212 was going to place its next piece and when it was going into the perception phase.

213 All participants replicated the three models while being filmed. Video
214 recordings were analyzed using The Observer software (version 15.0.1200, 2019).
215 We observed the completion time, number of errors (when a piece is placed,
216 removed, and replaced), and number of gestures, the latter defined as movements
217 of an upper limb (placing, removing a piece, managing the stock, thinking,
218 verification, waiting, robot interaction, and prevented gestures).

219 Finally, participants completed a translated version (Cegarra & Morgado,
220 2009) of the NASA-TLX (Hart & Staveland, 1988) to assess the cognitive load
221 they experienced (see Table 2). This test measures the experienced mental load
222 through six subscales: mental demand, physical demand, time demand, frustration,
223 effort. and performance. It is conducted in two stages (Hart & Staveland, 1988).
224 First, we asked participants to rate each subscale on a scale from 0 to 100. Second,
225 we asked them to rank the different subscales according to the impact of each one
226 on their overall feeling. This ranking ranges from 1 to 6, with 1 representing the
227 subscale with the lowest impact on the overall feeling and 6 representing the
228 subscale with the highest impact on the feeling of the mental load. All of this
229 information allowed us to obtain the weighted score of the cognitive load perceived
230 by each participant (each subscale is multiplied by the number of participants).

231

232 Table 2. French version of the NASA-TLX used in the experiment.

<i>Mental demand</i>	Quelle quantité d'activité mentale et perceptive a été nécessaire pour réaliser la tâche (par ex. réfléchir, décider, chercher, etc.) ? La tâche vous a-t-elle paru simple, nécessitant peu d'attention, ou complexe, nécessitant beaucoup d'attention ?
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<i>Physical demand</i>	Quelle quantité d'activité physique a été nécessaire pour réaliser la tâche (par ex. pousser, déplacer, tourner, manipuler, etc.) ? La tâche vous a-t-elle paru facile, peu fatigante, calme ou pénible, fatigante, active ?
<i>Temporal demand</i>	Quelle pression temporelle avez-vous ressentie durant l'exécution de la tâche ? Fallait-il gérer la réalisation de la tâche de manière lente ou de manière rapide ?
<i>Performance</i>	Comment estimez-vous votre performance en ce qui concerne la réalisation de la tâche ? (Quel est votre niveau de satisfaction concernant votre performance ?)
<i>Effort</i>	Quel effort (mental et physique) avez-vous dû fournir pour atteindre votre niveau de performance ?
<i>Frustration</i>	Vous êtes-vous senti satisfait, content, relaxé ou plutôt ennuyé, irrité, stressé pendant la réalisation de la tâche ?

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The questionnaire was implemented using the QUALTRICS software (Qualtrics, 2005). Internal consistency of the questionnaire was confirmed: no item was correlated more than 0.70 with another, the KMO index was greater than 0.50 (0.659), and the Bartlett Test was significant ($K=46.590(15)$, $p<0.01$). Study results were calculated using RStudio, version 1.4.1106 (RStudio Team, 2021). The results presented below are from a dataset available on GitHub (Datacobot2021a), and the specific open source code was applied (RcodeDatacobot2021a). Unpaired t tests were used to test the study hypotheses, with $p < 0.05$ considered statistically significant. Assumptions of normal distributions of equality of variances were tested, and the Wilcoxon test was used as relevant.

246

3. Results

247

3.1 Hypothesis 1: the effect of collaboration with a cobot on perceived cognitive load

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In the control condition, participants rated their cognitive load with mean of 37.5

250

out of 100 (SD=12.9, min=15.2, max=59.1, N=32) and in the experimental

251 condition at 35.5 out of 100 (SD=15.3, min=11.3, max=62.5, N=22). There was not
252 significant effect of collaboration with the robot on evaluation of cognitive load
253 ($t=0.51_{(52)}$, $p=0.61$).

254 ***3.2 Hypothesis 2: the effect of collaboration with a cobot on task completion time***

255 The participants took an average of 54.8 seconds (SD=18.5, min=19.4, max=146.4,
256 N=32) to reproduce a model in the control condition and 136.4 seconds (SD=30.9,
257 min=80.9 max=213.7, N=22) in the experimental condition. There was a
258 significant effect of collaboration with the robot on the completion time ($t=-$
259 $12.756_{(52)}$, $p=2,2*10^{-12}$). Oddly, the NASA TLX answers indicate that the
260 participants perceived less temporal demand in the collaboration condition
261 ($t=4.6_{(43.5)}$, $p=3,668*10^{-5}$).

262 ***3.3 Hypothesis 3: the effect of collaboration with a cobot on the number of errors***

263 Participants made an average of eight errors (SD=5.8, min=0, max=20, N=32) in
264 the control condition and two errors (SD=1.8, min=0, max=6, N=22) in the
265 experimental condition. There was a significant effect of collaboration with the
266 robot on the number of errors ($w=618.5$, $p=2,556*10^{-6}$).

267 ***3.4 Hypothesis 4: the effect of collaboration with a cobot on the number of*** 268 ***gestures performed***

269 The participants performed an average of 74 gestures (SD=20, min=41, max=124,
270 N=32) in the control condition and 51 (SD=9.8, min=34, max=72, N=22) in the
271 experimental condition. There was a significant effect of collaboration with the
272 robot on the number of gestures ($t=4.9547_{(52)}$, $p=8,068*10^{-6}$).

273 We tested the effect of the collaboration on all sub-sections of the NASA
274 TLX test. T-tests revealed no differences on those sub-sections (including

275 perceived frustration and effort), with the exception of a positive significant effect
276 of the collaboration on the perceived time demand.

277

278 **4. Discussion**

279 The current results concerning the reduction of the number of errors and
280 the number of gestures in the collaboration condition are in line with our initial
281 hypothesis (H3 and H4). In our study, the human/robot collaboration reduced the
282 number of errors and the number of gestures performed. This outcome could imply
283 that in a non-experimental industrial work task, collaboration with a cobot could
284 improve operator efficiency and the quality of their work. Similar results have been
285 reported earlier. Indeed, Salunkhe et al. (2019) recently found that cobots could, in
286 theory, identify problematic gestures, thus protecting human workers, while
287 improving the quality of the work.

288 Since introducing the cobot increased the number of instructions
289 (participants had to understand the task, and understand how the cobot works and
290 how to interact with it), we feared that those additional instructions would
291 adversely impact perceived cognitive load. However, this was not the case, since
292 the perceived mental loads did not differ in the two conditions and H1 was not
293 supported, though collaboration with the cobot had no negative effect on perceived
294 cognitive load. Kildal et al. (2019) found that the complexity of the task is not
295 increased due to the introduction of a collaboration between human and cobot,
296 even when the operator is cognitively impaired. Future studies need to measure the
297 impact of collaborating with a cobot on cognitive load, as it is representative of the
298 operator's wellbeing in their work (Fruggiero et al., 2020).

299 Finally, the results concerning completion time (H2) were against our
300 expectations. Indeed, we found that completion time significantly increased in the
301 condition of co-activity. This increase was due to the introduction of waiting time

302 and technical problems that occurred during the experiment. In fact, another
 303 study, realized in an industrial context, showed no increase in completion time
 304 between collaboration with a cobot and no collaboration (Fager et al., 2019).
 305 Nonetheless, the perceived time demand was significantly lower here in the
 306 experimental condition. Thus, even though collaboration with the cobot lasted
 307 longer, this was not reflected in the perceptions of the participants. This outcome
 308 could be a clue that perceived pleasure with a cobot is higher than the perceived
 309 pleasure of working alone (El Makrini et al., 2018). Overall, we concluded that
 310 collaboration improved the user experience on the following criteria: errors,
 311 gestures and perceived time demand (Table 3).

312 Table 3. Summary of the results of collaborating with a cobot for each independent
 313 variable.

Outcome	Collaboration with cobot
Perceived cognitive load	Equal to the control condition
Completion time	Higher than in the control condition
Number of errors	Lower than in the control condition
Number of gestures	Lower than in the control condition
Perceived time demand	Lower than in the control condition

314
 315 This study provides several contributions regarding human-machine
 316 systems design. Indeed, we noticed that there are variabilities in human behavior
 317 during the realization of a laboratory-simulated assembly task. These variabilities
 318 emerged from organizational design (presence or absence of a cobot), technical
 319 variability (issues linked to the cobot on certain experimental runs), and inter-
 320 individual variabilities (e.g. wide range of the number of gestures performed by
 321 participants).

322 These variabilities were managed within the collaboration, as was the case
323 in other recent studies (Chacón et al., 2020; Fager et al., 2019). The cobot and its
324 AI allowed the experimental task to be constrained in terms of how the assembly
325 was done (what piece to put, the order of piece, etc.) only by the human participant
326 and not by “the machine”. Our work shows that it is possible to have an intelligent
327 machine that regulates its actions to help the human, whatever strategy he adopts,
328 which is an advantage for industry work (Pauliková et al., 2021). Furthermore, the
329 current work showed that this new type of collaboration could be beneficial in
330 terms of performance and usability. Further studies in an industrial setting, though,
331 are needed to confirm such benefits. Those studies need to address the impacts
332 (negative and positive) that cobots have on the operators (well-being, health,
333 satisfaction at work) and on the industry (performance, security), the protocol of
334 implementation used to change the organization of work, how operators are trained
335 and recruited to work with cobots, and the ethics behind those changes. There
336 needs to be an emphasis on the study of social aspects of the human/cobot
337 collaboration.

338 We have also verified that it is possible (in the context of a laboratory task)
339 to measure cognitive load through different behavioral measures and to use these
340 same indicators to obtain information on usability criteria according to the ISO
341 9241-11. Investigating cognitive load needed to adapt cobots to the human is a
342 new, challenging, and necessary field of research (Fruggiero et al., 2020). It is,
343 therefore, an original contribution to bring together these two concepts belonging
344 to different disciplinary fields and by experimenting in a different domain of UX.
345 We offer an original experimental protocol that can be transposed to other types of
346 tasks.

347 The cobot had technical problems that impacted some experimental runs.
348 By working on improving of the cobot’s technical capacities, we will be able to
349 reduce task completion time and thus improve the overall UX. Furthermore, it

350 would be interesting to replicate this study in an industrial environment, which is
351 more complex than laboratory-controlled situations. The task here was quite
352 simple, thus limiting the generalizability of the study. However, this simplicity was
353 necessary to improve the AI of the cobot, a first step to ensure that AI was able to
354 adapt to the variabilities of the human.

355 Our work indicates that the adaptation of a robotic system to a human is
356 possible and should receive priority consideration owing to its benefits: it requires
357 very little training (since the human does not adapt to the cobot) and it is flexible to
358 human variabilities. Also, no analysis was made regarding potential differences
359 related to gender, as there were more women than men in our study (statistical
360 analysis would have been biased). Future studies should address gender (Perez,
361 2019) as a potential source of interindividual variability as it is relevant to improve
362 science and design (Tannenbaum et al., 2019).

363 An experiment with a within-subjects design, by randomizing the order of
364 the two conditions, would allow us to assess the perception of difference between
365 the two conditions. Indeed, participant behaviors were different across
366 experimental conditions. For example, the participants were much more static in
367 the experimental condition than in the control condition. This difference in
368 behavior could be the result of a different conceptualization of the task.

369 Future research needs to be developed to evaluate the impact of the cobot
370 collaboration on workload. For now, our study is in line with earlier literature, and
371 it seems that using a cobot to collaborate with an operator could decrease perceived
372 cognitive load. As Perre et al. (2018) suggested in their article, the cobot could
373 “diminish an operator’s workload and improve the working conditions” (p. 5). To
374 analyze this impact, researchers can use self-reported scales such as the NASA-
375 TLX and behavioral measurements such as the number of errors and the
376 completion time.

377 In summary, we found that performing an assembly task in collaboration
378 with a cobot increased effectiveness, maintained the level of satisfaction, and
379 improved certain criteria of efficiency (number of errors, number of gestures) if the
380 robot is programmed to adapt its decisions to the human's. In this laboratory
381 context, the human/cobot collaboration facilitated better task performance and an
382 overall improved UX. We also developed an experimental protocol linking the
383 concepts of usability and cognitive load in a multidisciplinary experimental task,
384 combining the technical constraints of programmers and the constraints of human
385 behavior measurements. This protocol can be used in future studies to identify key
386 points to consider when designing a cobot (perception of the cobot, infrastructure
387 of the AI, etc.), thus facilitating broader and more effective implementation of
388 cobots in Industry 4.0.

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