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Title: Proof of concept of a cobotic system in a constrained work environment.

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Structured abstract

Objective: This study is a proof of concept that aims to measure the impacts of a human/cobot collaboration on the human and his task during a simulated chemistry assembly.

Background: The 5th industrial revolution calls for refocusing work on the human operator, placing him or her at the center of the system. Thus, cobotic systems are increasingly implemented to support human work. In this research, we study the impact of a real-life cobot on the performance (e.g. number of errors, time completion), workload, risk exposure and acceptability of participants realizing an industrial-like assembly task.

Method: Participants had to reproduce an assembly model with Duplos in collaboration with a cobot in a laboratory setting. The effect of the human expertise on the task (prior to the collaboration) and the level of cobot adaptation to human safety constraints on the performance at the task and on operator were tested.

Results: The main results report that expert participants did less mistakes and were less exposed to risks than non-experts. However, both of them succeeded in the task thanks to the cobot adaptation. Also, the cobot was able to adapt to human safety constraints. This adaptation led participants to expose themselves to fewer risks. Also, contrary to previous findings, experts had a similar score of acceptability than non-experts.

Conclusion: This laboratory experiment is a proof of concept demonstrating that using a cobotic solution could potentially assist humans in supporting high-risk work operations.

Application: Cobotic system designers and work designers could benefit from this research's exploratory results when supporting the design of constraints in workstations for high-risk work operations.

Keyword: cobots, human-machine collaboration, risk exposure

1. Introduction

The industry 5.0 calls for a paradigm shift from the actors of the industrial sectors (Xu et al., 2021). This industry “recognizes the power of industry to achieve societal goals beyond jobs and growth, to become a resilient provider of prosperity, ensuring that production respects the limits of our planet and placing the well-being of the industrial worker at the center of the production process” (European Commission, 2021, p. 5). The European Commission (2021) supports collaborative technologies such as collaborative robots (cobots) to place the human resource in the center of the production. Therefore, collaborative robotic systems are implemented in the industrial work system to enhance efficiency and human well-being at work (Knudsen & KaiVo-Oja, 2020). The term “cobotic system” is used to illustrate the collaboration between a human worker and a cobot or collaborative robot (Colgate et al., 1996). Cobots are robots designed to work on a task in a shared environment in collaboration with a human (Peshkin & Colgate, 1999). Their abilities to adapt to the operator could help dealing with variabilities at work (Hiatt et al., 2011). Studies have shown that this adaptation is able to induce less physical effort (Varrecchia et al., 2023), less errors (Fournier et al., 2022), less exposure to risks (Pauliková et al., 2021), a lower workload (Chan et al., 2020) and a better output quality (Fournier et al., 2024). However, because of its difficulties to adapt to human constraints, cobotic systems can also lead to negative consequences (Cheon et al., 2022; Fournier et al., 2022; Schoose et al., 2023) like decreasing work precision and perceived work quality (Schoose, 2022). Different work situations were analyzed in the context of a cobotic implementation (e.g. maintenance workers, production line workers), while other have not been studied at all (e.g. chemists). Yet, chemistry is a risky activity, and the resulting variabilities can have negative impacts on the operator and his work (Bayram & Bilim, 2012; Garden, 1962; McNair, 2006; Sung et al., 2020; Triolet et al., 2002). And, studies have suggested that a cobotic collaboration could help reduce those negative impacts (Fournier et al., 2023; Tokatli et al.,

2021). Also, Béguin et al. (1999) have proven that intelligent technologies can reduce the operator's risks exposure. It has not been done using cobotic collaboration. It is important to determine if chemists will expose themselves to less risks if the cobot adapts to the safety constraints and human variability. Indeed, chemists have different strategies realizing a chemical task (Fournier et al., 2023).

Even though cobotic systems could be beneficial to the work and the operator, considering technology acceptance is key to determine its use (Cippelletti, 2017; Nielsen, 1994; Venkatesh et al., 2003, 2012). The acceptance of a technology have been studied with different models, such as the Unified Theory of Acceptance and Use of Technology (UTAUT) that predicts 56% of behavioral intention (Venkatesh et al., 2003). Later the authors updated their model with other dimensions and predicted 74% of behavioral intention and 52% of use behavior (Venkatesh et al., 2012). In this adapted model (UTAUT2), the precursors of the intent of use are performance expectancy (or perceived usefulness), effort expectancy (or perceived ease of use), social influence, facilitating conditions, hedonic motivation (or pleasure perceived), price value and habit of using technology. Finally, the precursor of "use" is the "intent of use". The table below illustrate the different dimensions and their definitions (Table 1).

Table 1. Definition of the dimension of the UTAUT2

Dimension of UTAUT2	Definition
Performance expectancy (perceived usefulness)	"The degree to which using a technology will provide benefits to consumers in performing certain activities" (Venkatesh et al., 2012, p. 159)
Effort expectancy (perceived ease of use)	"The degree of ease associated with consumers' use of technology" (Venkatesh et al., 2012, p. 159)

Social influence	“The extent to which consumers perceive that important others (e.g., family and friends) believe they should use a particular technology” (Venkatesh et al., 2012, p. 159)
Facilitating conditions	“Consumers’ perceptions of the resources and support available to perform a behavior” (Venkatesh et al., 2012, p. 159)
Hedonic motivation (pleasure perceived)	“The fun or pleasure derived from using a technology” (Venkatesh et al., 2012, p. 161)
Price value	“Consumers’ cognitive tradeoff between the perceived benefits of the applications and the monetary cost for using them” (Venkatesh et al., 2012, p. 161)
Habit	“Self-reported perception” of the habits of using technology (Venkatesh et al., 2012, p. 162)

The authors also tested moderators such as the experience of the respondent. The expertise of the operator mediates the acceptability of the system in other studies (Cippelletti, 2017). The authors found that more experienced workers did not accept as well as novice workers the technology implemented. Also, a more recent study has found that “the ease of use and perceived safety have a positive influence on the intention to use a cobot at work” (Cippelletti et al., 2024, p.10). A measure of trust in the human/cobot collaboration is also needed because it is lacking in the literature (Kaplan et al., 2023; Martin, 2018).

Therefore, the aim of this study is to be a proof of concept measuring the impacts of a human/cobot collaboration on the human and his task during a simulated chemistry assembly. More precisely, the experiment will test whether the operator success in a task (Fournier et al., 2022; Schoose et al., 2023), the completion time (Fager et al., 2019; Fournier et al., 2022; Mariscal et al., 2023), the number of errors (Fournier et al., 2022; Mariscal et al, 2023) and the number of risk exposures are different depending on whether the operator is working with a

cobot that adapts to safety constraints or with a cobot that does not adapt to those constraints. Also, the level of expertise can affect the acceptability of the technology and the task itself (Cippelletti, 2017). Therefore, there is a need to determine if the cobot can adapt to experts and non-experts to achieve the task. If the cobot adapts to the expertise, there should not be any difference in terms of number of errors, risk exposure and success between experts and non-experts. The impact of cobot adaptation on human workload, which is the amount of mental resources used for a specific task, is also important to measure (Verhulst, 2018). Indeed, a reduced mental workload is interesting for the industry 5.0 as it required to increase the operator's wellbeing at work (European Commission, 2021).

Considering the different research questions, we address in this work several hypotheses:

H1: The operator's **expertise** (expert vs non-expert) has an effect on the operator and his task during a cobotic collaboration.

H1a: Experts have a lower level of acceptability than non-experts (supported by Cippelletti, 2017).

H1b: The operator expertise has an effect on the number of errors.

Indeed, due to their training, the experts should make less errors than non-experts.

H1c: The operator expertise has no effect on the success of the task.

Indeed, the cobot should adapt itself to the level of expertise of the participant. It should ensure that the task is succeeded whatever the level of expertise.

H1d: The operator expertise has an effect on the number of risk exposures.

Indeed, due to their training, the experts should expose themselves to less risks than non-experts.

H1e: The operator expertise has no effect on the workload.

Indeed, the cobot should adapt itself to the level of expertise of the participant. It should ensure that the workload stays low whatever the level of expertise.

H2: The **degree of cobot adaptation** (adapt to the human's constraints vs does not adapt) has an effect on the operator and on his task.

H2a: Operators have a lower workload when the cobot adapts to their constraints than when it does not.

H2b: Operators make less errors when the cobot adapts to their constraints than when it does not.

H2c: Operators have a higher level of acceptability when the cobot adapts to their constraints than when it does not.

H2d: Operators are less exposed to risks when the cobot adapts to their constraints than when it does not.

H3: There is an interaction between the effect of the **degree of cobot adaptation** and the effect of the **expertise** of the participant.

2. Method

2.1. *Experimental setup*

In this study, we have created a task which tends to reproduce the activity of a chemical operator: assemble chemical products with variable degrees of risk involved. In this context, participants had to wear surgical gloves to handle some dangerous products in the same way as chemists (Fournier et al., 2023). The “chemical products” were Duplo pieces and the “chemical mix” was the completion of a given model (Cf. Figure 1). All participants had to reproduce a Duplo model composed of 4 different colors and 5 floors. For technical reasons, participants

had to realize the model floors by floors. Indeed, they could put pieces for the second floor only when the first one was completed.



Figure 1. A photograph of the experimental setup with a participant realizing the task with the collaborative robot YuMi

To study the adaptation to safety constraints, we had to simulate danger exposure. For this, red blocks were presented as very dangerous and to be touched only with thicker gloves (just as chemists do, see Fournier et al., 2023).

2.2. Participants

38 adult participants (30 females and 8 males) without any color vision impairment and with no pain in the upper limbs participated in the study. It lasted approximately one hour for each participant. 34 were right-handed and 4 were left-handed. They were recruited by a post on the university's website. Students were awarded points in certain courses. 34 out of 38 participants declared not being used to work with robots. 19 participants were randomly placed in the condition "expert" and 19 in the condition "non-expert". Contrary to the non-experts,

expert realized the experimental assembly three times alone (without cobot) before working with the cobot. In fact, during the pre-tests, it was only after three model executions that participants stopped making errors and no longer needed help. 19 participants were randomly placed in the condition “adaptation of the cobot” and 19 in the condition “non-adaptation”. In the condition of adaptation, the cobot associates a constraint (a cost) to a human risk exposure. It acts to minimize the human risk exposure. In the condition of non-adaptation, the cobot participates in the task without knowing the existence of any constraints. All participants succeeded the experimental task which is described below.

2.3. Procedure

All participants (experts and non-experts) realized one simple assembly task with the cobot as training (Cf. Figure 2).

ACCEPTED MANUSCRIPT (Applied Ergonomics)

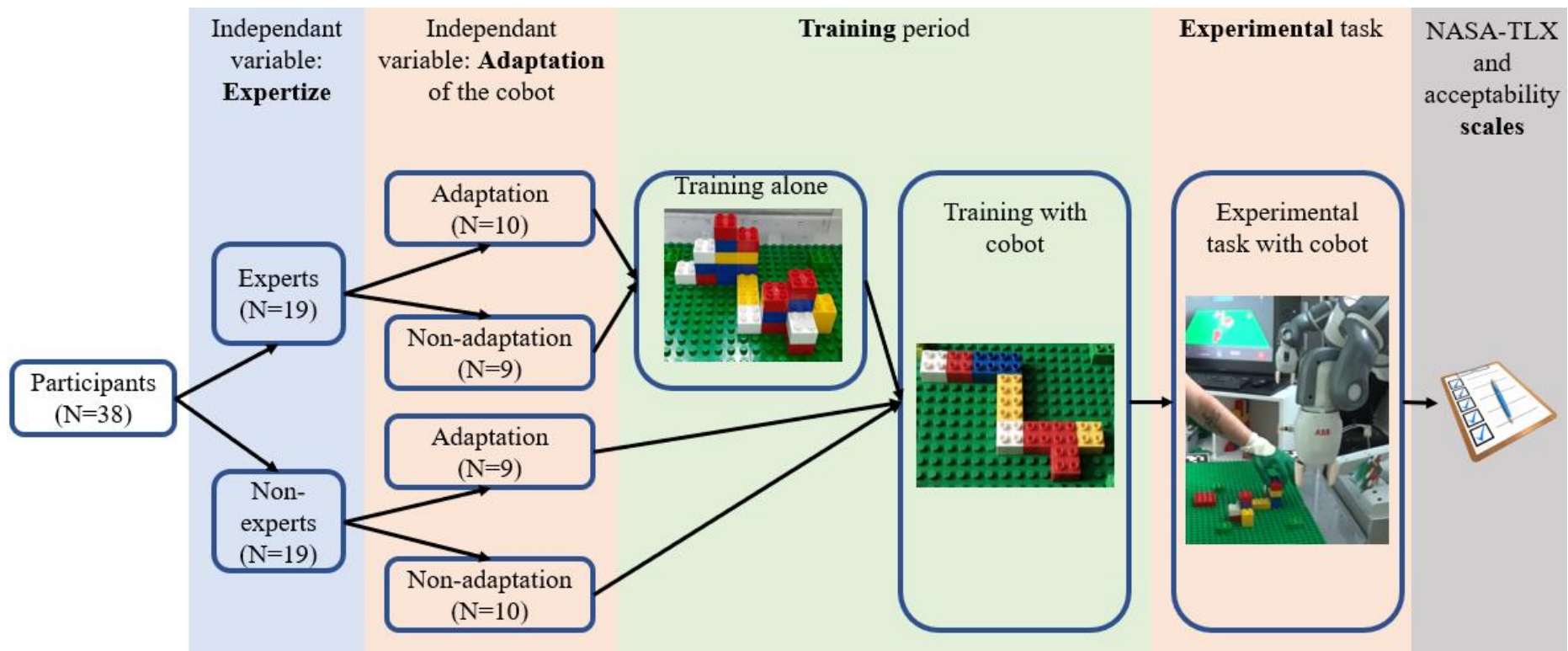


Figure 2. Presentation of the different conditions and experimental procedures

ACCEPTED MANUSCRIPT

All the participants had to reproduce a Duplo model. A total of two models were presented (Cf. Figure 3): the training model, labelled as “A” (used to train all participants to work with the cobot), and the experimental model, labelled as “B”, that all participants had to reproduce with the cobot (it was also used to train the experts before they collaborated with the cobot).

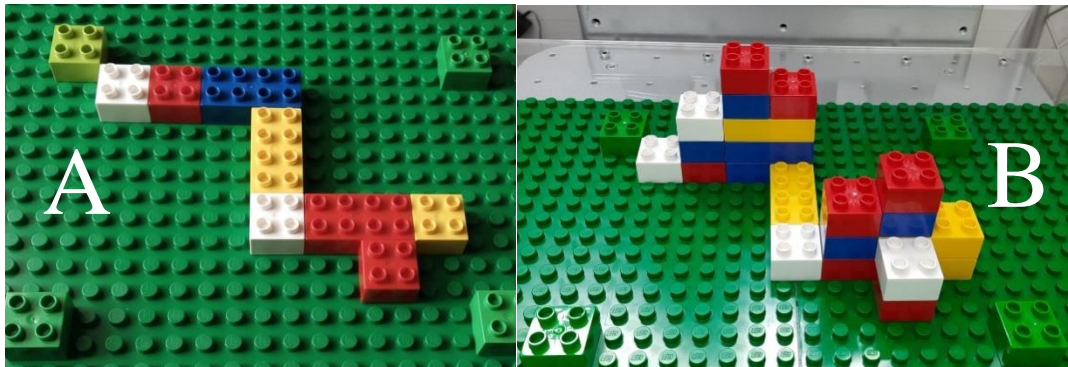


Figure 3. The training model (A) and the experimental model (B) used in the experiment

After the training session, all of the participants realized the experimental task with the cobot. The participant reproduced the experimental model in a precise area (Cf. area 1 in Figure 4) with the cobot as fast as possible while answering simple math additions to mimic a complex work situation with multiple demands. In both conditions, the participant had access to more than half of the Duplo’s stock (Cf. area 2 in Figure 4). The cobot had access to the remaining of the Duplo’s stock (Cf. areas 3 in Figure 4).

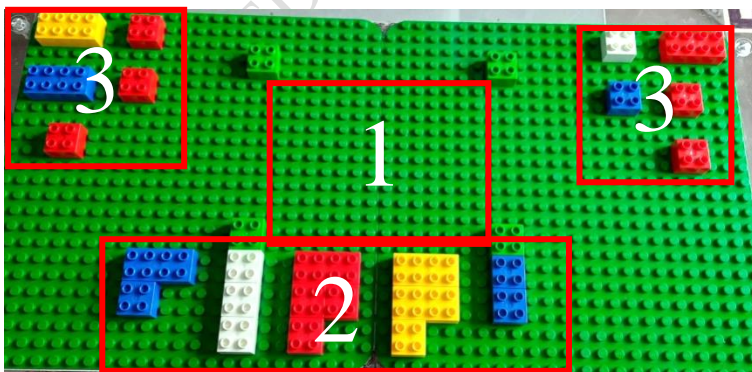


Figure 4. Complex task distribution (1: work area; 2: human stock; 3: cobot stock)

2.4. Measures and material

We used different indicators to test our hypotheses. Our indicators of performance are the number of errors (piece placed and replace elsewhere), the completion time (the completion time of the model) and the percentage of success of the model (the model is correct). Our indicator of workload is the NASA TLX score (Hart, 2006; Hart & Staveland, 1998; Rubio al., 2019; Webb al., 2021; Cf. Table 2).

Table 2. Dimensions and items of the NASA-TLX questionnaire (Hart & Staveland, 1998)

Dimension	Item
Mental workload	How mentally demanding was the task?
Physical demand	How physically demanding was the task?
Time demand	How hurried or rushed was the pace of the task?
Performance	How successful were you in accomplishing what you were asked to do?
Effort	How hard did you have to work to accomplish your level of performance?
Frustration	How insecure, discouraged, irritated, stressed, and annoyed were you?

This questionnaire was assessed on LimeSurvey using the SCREEN platform (*Service Commun de Ressources pour l'Expérimentation et l'Équipement Numérique*) managed by Grenoble Alpes University. Our indicator of acceptability is the score of an acceptability questionnaire derived from Venkatesh & Bala (2008) and Cippelletti et al. (2024). This questionnaire is measuring 6 indicators of the acceptability (trust perceived, pleasure perceived, usefulness perceived, coherence for the task perceived, social influence perceived and the ease of use perceived). Our indicator of risk exposure is the number of times the participant touches a « dangerous » block (red block). We also observed the position (on which level) where the risk exposure takes place. If it takes place during the construction of the first level (first floor of the model), it means that the participant exposed himself to some risk very soon during the task. If it happens at the last level, it means that the participant exposed himself to some risk as last resort.

The robotic environment set up for experimentation is detailed in Hmedan et al. (2022; Cf. Figure 5).

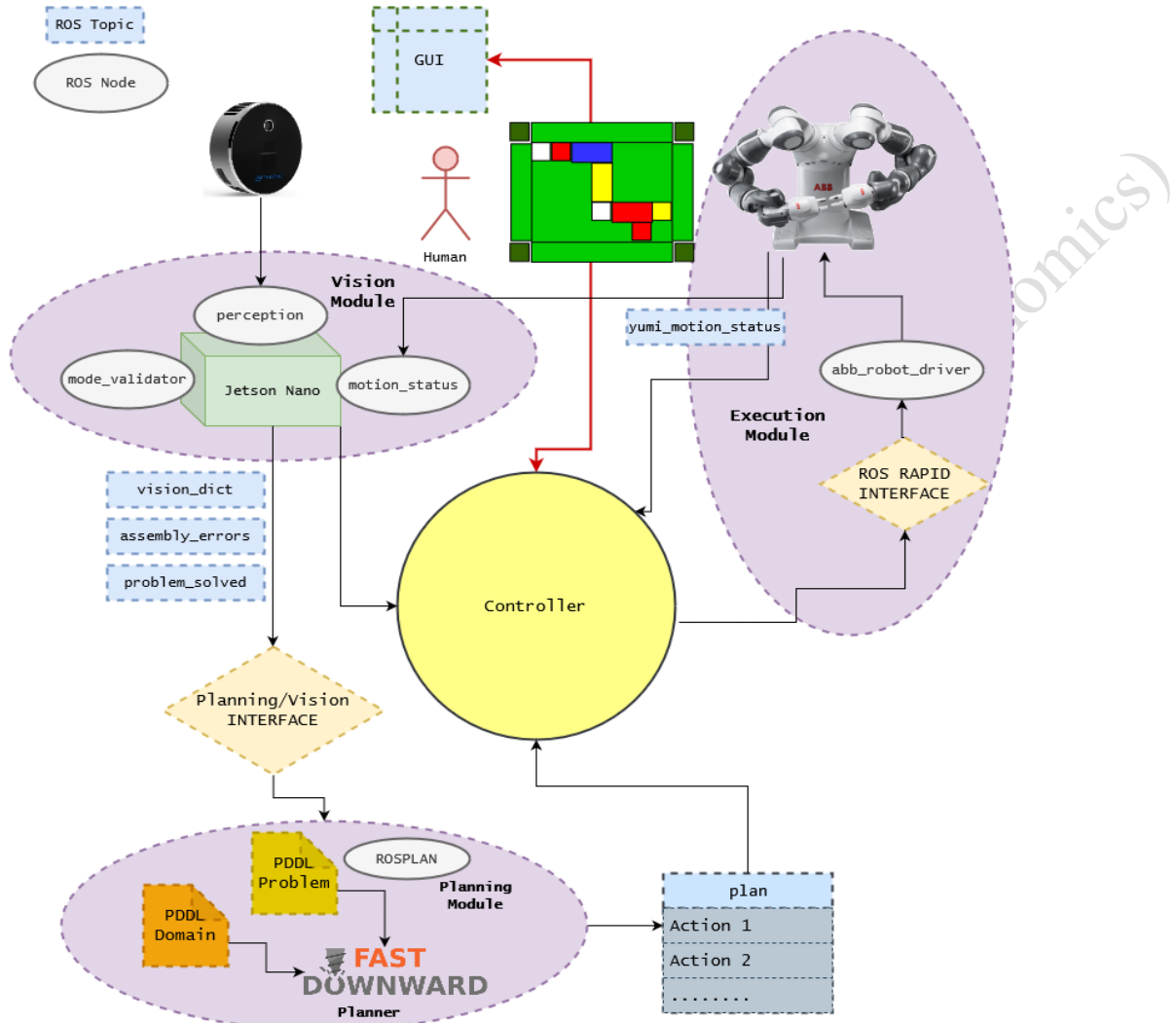


Figure 5. Diagram of the robotic system setup used in the experiment.

The setup comprises a collaborative robot, YuMi (ABB), which is configured via the ROS Rapid interface. Additionally, it includes a Vision Module utilizing a Jetson Nano camera and a Vision Interface programmed to handle perception of changes and assembly errors, while coordinating with the motion status of YuMi. A task planning interface, based on PDDL, Planning Domain Description Language (Ghallab et al., 1998), is utilized for continuous adaptation of robot behavior in response to perception and human interaction. The Planning solution is managed by the state-of-the-art Solver PDDL4J (Pellier & Fiorino, 2018),

employing hierarchical planning to determine the optimal sequence of tasks for the robot to execute, thereby minimizing human exposure. Acting as the system's central control unit, it dictates tasks to the robot and provides guidance to humans. A Graphic User Interface facilitates human-robot communication, providing crucial system status updates, task suggestions, and enabling users to request assistance from the robot. Finally, a controller orchestrates data flow between the various modules, ensuring effective communication and coordination. Under non-adaptive conditions, the robot will autonomously decide which block to move without considering any constraints. Conversely, under adaptive conditions, the robot will prioritize moving red blocks to mitigate human risk, effectively responding to identified constraints.

2.5. Statistical analysis

Descriptive statistics such as means and standard errors are reported in the results section (see section 3). To test the effect proposed in the different hypothesis, Student T-tests were used. Parametric tests were used to achieve greater statistical power and assumptions (e.g. normal distribution, homogeneity of variance) were met. When an effect was found, a Cohen'D was used to have the effect size. Also, to test the proposed interaction effect (H4), a generalized repeated-measures mixed model was run. R-Studio (1.4.1106 version) was used to perform all tests.

3. Results

3.1. Questionnaire validity

A test was performed to assess the reliability of the NASA-TLX: the result was satisfying with a Cronbach superior to 0,76.

A test was performed to assess the reliability of the Acceptability questionnaire: the result was satisfying with a Cronbach superior to 0,9. All the scales tested separately had Cronbach's score superior to 0,78. A factor analysis was performed to make sure than the scales

used were measuring independent factors. The test identified 6 different factors that predicted more than 84% of the scores' variability (Cf. Table 3).

Table 3. Number of components and explained variance by the factor analysis

Component	Total	% of variance	% cumulated
1	3,821	16,614	16,614
2	3,746	16,287	32,900
3	3,595	15,628	48,529
4	3,082	13,401	61,929
5	2,809	12,212	74,141
6	2,340	10,175	84,316

Those 6 factors are the one we predicted: trust perceived, pleasure perceived, usefulness perceived, coherence for the task perceived, social influence perceived and the ease of use perceived (Cf. Table 4).

Table 4. Factor loadings of the factor analysis by principal component analysis

	1	2	3	4	5	6
Trust3	,897					
Trust1	,895					
Trust2	,887					
Trust4	,816					
Pleas1		,913				
Pleas4		,893				
Pleas2		,889				
Pleas3		,723				
Pleas5		,566				
Usefu2			,891			
Usefu3			,887			
Usefu4			,825			

Usefu1	,775
Coher1	,905
Coher2	,887
Coher3	,840
Influ3	,950
Influ2	,926
Influ1	,862
Usabi2	,863
Usabi3	,820
Usabi1	,643
Usabi4	,484

3.2. H1: The operator's expertise (expert vs non-expert) effects

Table 5. Means and standard-errors of all the dependent variables tested classified as “expert” or “non-expert”

Condition	Ease of use	Coherence	Pleasure	Usefulness	Influence	Trust	Accept
Expert	M=21.95 (SD=3.82)	M=16,84 (SD=3,69)	M=27,42 (SD=6,27)	M=17 (SD=5,99)	M=13,74 (SD=4,18)	M=20,16 (SD=4,6)	M= 19,52 (SD= 2,56)
Non-expert	M=21.21 (SD=4.6)	M=16,26 (SD=4,09)	M=27 (SD=8,08)	M=17,95 (SD=6,39)	M=13,21 (SD=4,55)	M=21,68 (SD=5,37)	M= 19,55 (SD= 3,97)
Condition	Errors	Risks	Glove level	Workload			
Expert	M=0,84 (SD=1,07)	M=1,53 (SD=0,7)	M=3,42 (SD=1,57)	M=20,16 (SD=4,6)			
Non-expert	M=2,42 (SD=3,11)	M=2,05 (SD=0,78)	M=2,11 (SD=1,59)	M=21,68 (SD=5,37)			

H1a: Experts have a lower level of acceptability than non-experts.

There is no significant effect of the participant's expertise on the acceptability score ($T(36) = -0,03239$; $p = 0,9743$). There is no effect of the participant's expertise on all the different subscales of the acceptability questionnaire (Cf. Figure 5).

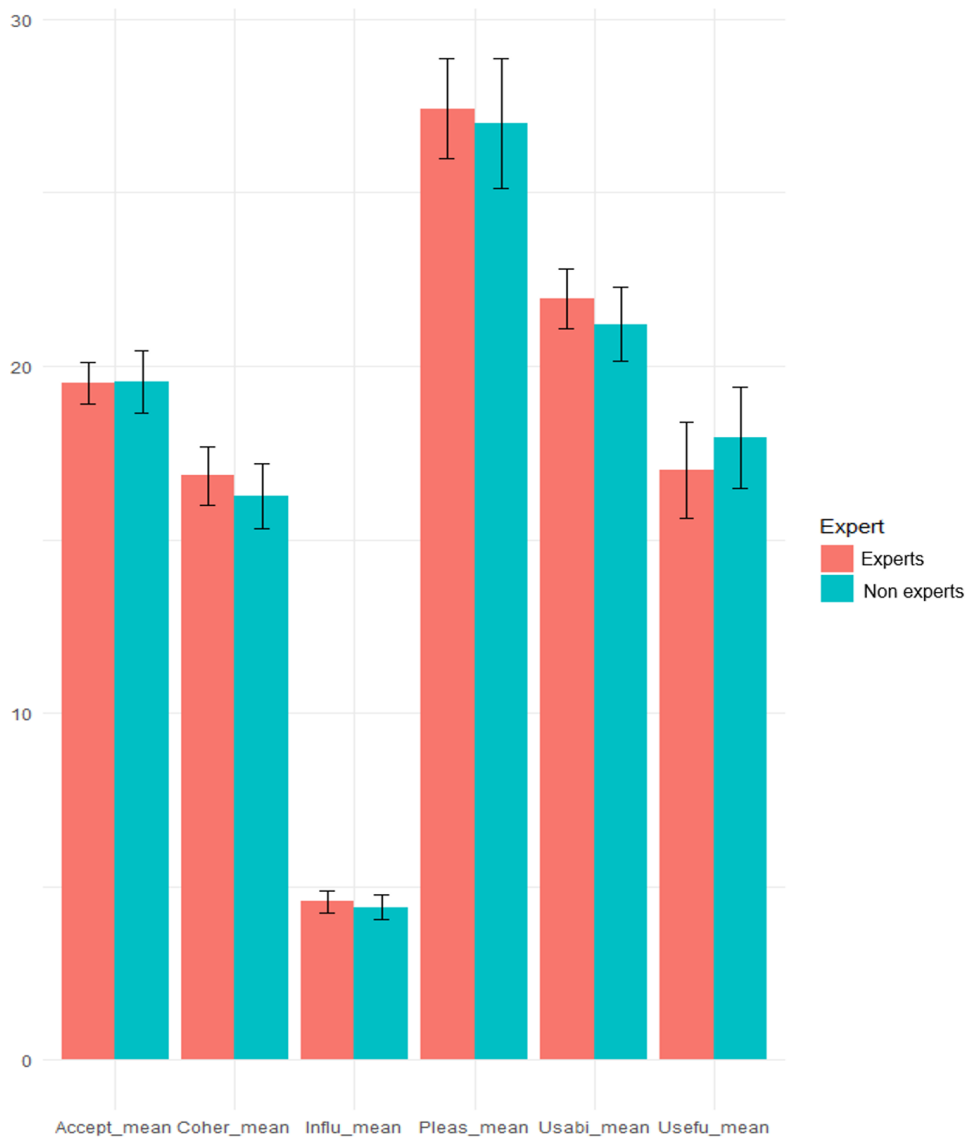


Figure 6. Means scores of experts and non-experts on the different acceptability scales

H1b: The operator expertise has an effect on the number of errors.

There is a significant effect of the participant's expertise on the number of errors ($T(22,174)=-2,090;p=0,048$). Expert participants do less mistakes than non-experts (Cf. Figure 6). The Cohen's D is $-0,6781501$ (medium effect).

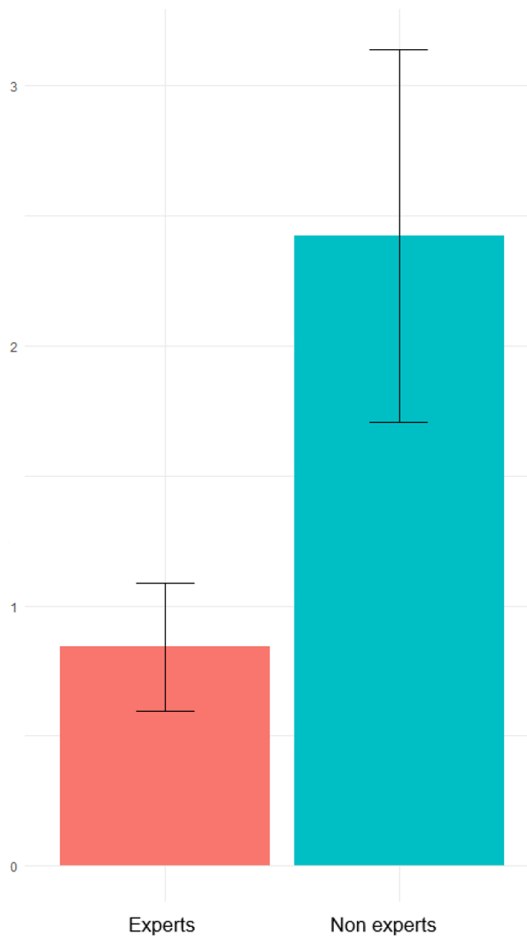


Figure 7. Means of the number of errors made by experts and non-experts

H1c: The operator expertise has no effect on the success of the task.

The operator expertise has no effect on the success of the task as all the participants have succeeded in the assembly task. The cobot adapted to the human operator to ensure the success of the task as hypothesized.

H1d: The operator expertise has no effect on the number of risk exposures.

There is a significant effect of the participant's expertise on the number of risk's exposure ($T(36)=-2,194;p=0,035$). Expert participants expose themselves to less risks than non-experts (Cf. Figure 7). The Cohen's D is $-0,7117683$ (medium effect). There is a significant effect of the participant's expertise on the level number on which participants first put their gloves ($T(36)=2,559;p=0,015$). Expert participants put their gloves later than non-expert participants. The Cohen's D is $0,8302385$ (large effect).

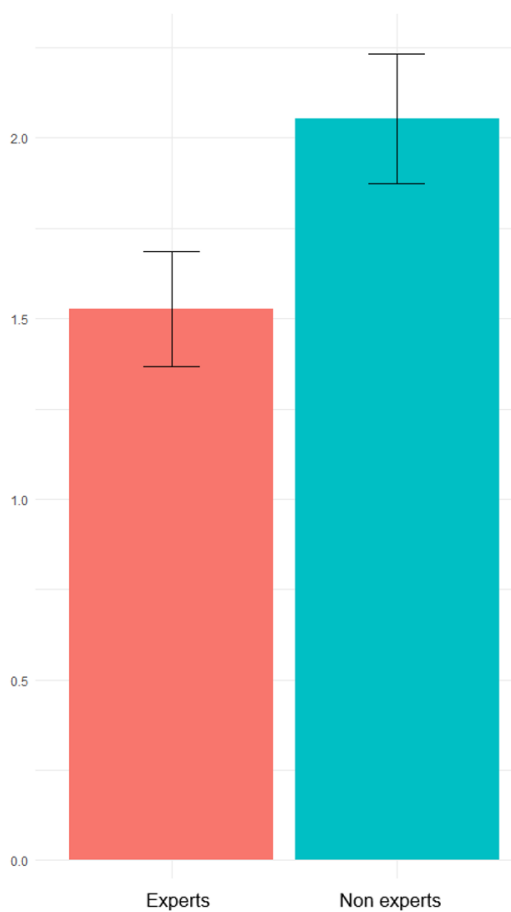


Figure 8. Means of number of risk exposure of experts and non-experts.

H1e: The operator expertise has no effect on the workload.

There is no significant effect of the participant's expertise on the acceptability score ($T(36)= -1,278; p= 0,2094$). The cobot adapted to the level of expertise of the participant.

3.3. H2: The degree of cobot adaptation (adapt to the human's constraints vs does not adapt) has an effect on the human and on his task.

Table 6. Means and standard-errors of all the dependent variables tested classified as “adaptation” or “no adaptation”

Condition	Ease of use	Coherence	Pleasure	Usefulness	Influence	Trust
Adaptation	M=21,21 (SD=4,48)	M=16,63 (SD=4,27)	M=26,37 (SD=8,11)	M=17,74 (SD=5,14)	M=13,05 (SD=4,7)	21,26 (SD=5,37)
No adaptation	M=21,95 (SD=3,96)	M=16,47 (SD=3,5)	28,05 (SD=6,11)	M=17,21 (SD=7,11)	M=13,89 (SD=4)	20,58 (SD=4,69)
Condition	Workload	Errors	Risks	Accept	Glove level	
Adaptation	M= 120,66 (SD=62,07)	M= 1,11 (SD=2,26)	M= 1,42 (SD=0,69)	M= 19,38 (SD= 3,84)	M= 3,42 (SD= 1,64)	
No adaptation	M= 129,95 (SD=64,18)	M= 2,16 (SD=2,54)	M= 2,16 (SD=0,69)	M= 19,69 (SD= 2,74)	M= 2,11 (SD= 1,52)	

H2a: Operators have a lower workload when the cobot adapts to their constraints than when it does not.

There is no effect of the adaptation of the cobot on the perceived workload ($T(36)=-0,45352; p=0,6529$).

H2b: Operators make less errors when the cobot adapts to their constraints than when it does not.

There is no effect of the adaptation of the cobot on the number of errors ($T(36) = 1,3487; p = 0,1858$).

H2c: Operators have a higher level of acceptability when the cobot adapts to their constraints than when it does not.

There is no significant effect of the degree of adaptation on the acceptability scores ($T(36) = 0,29185; p = 0,7721$). There is no effect of the participant's expertise on all the different subscales of the acceptability questionnaire. Figure 8 presents the descriptive results of the questionnaire.

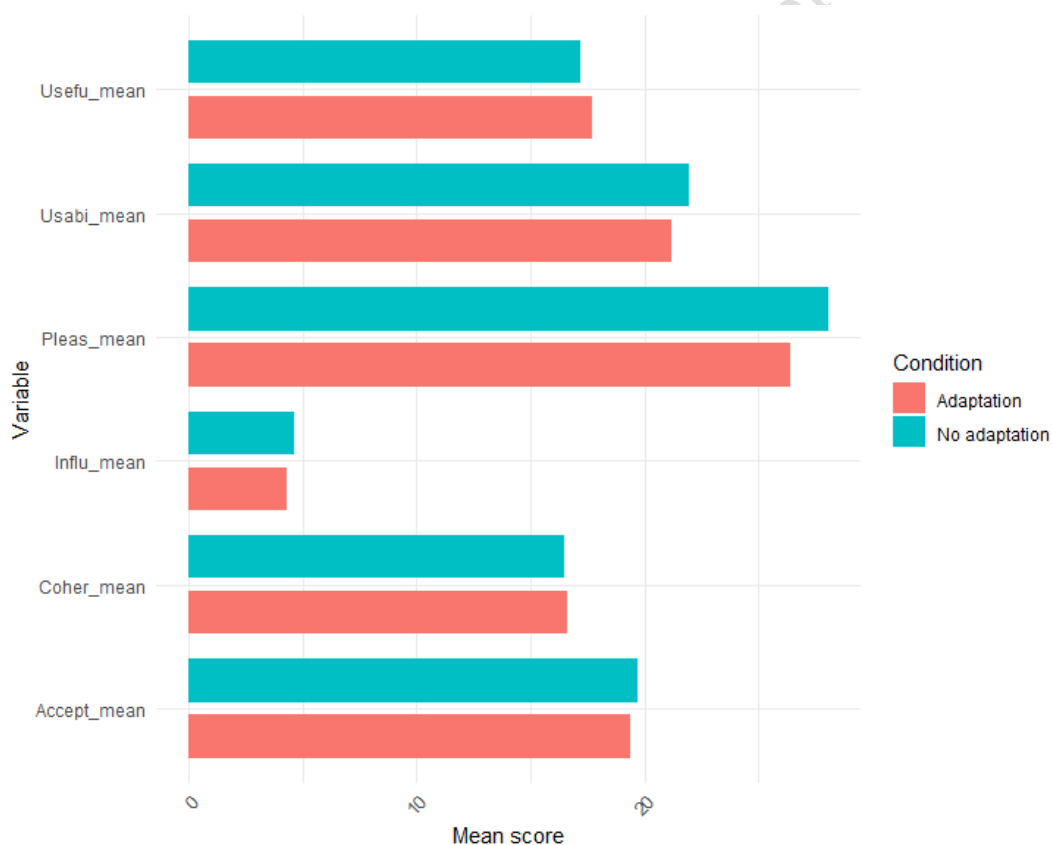


Figure 9. Means scores of participants in the adapted cobot condition and participants in the non-adapted cobot condition on the different acceptability scales

H2d: Operators are less exposed to risks when the cobot adapts to their constraints than when it does not.

There is a significant effect of the degree of adaptation on the number of risks taken ($T(36)=-3,2897;p=0,002249$). Participants take more risks when the cobot doesn't adapt to their constraints (Cf. Figure 9). The Cohen's D is $-1,067318$ (large effect). There is a significant effect of the degree of adaptation on the level number on which participants first put their gloves ($T(36)=2,559;p=0,015$). Participants put their gloves later when the cobot adapts to their constraints. The Cohen's D is $0,8302385$ (large effect).

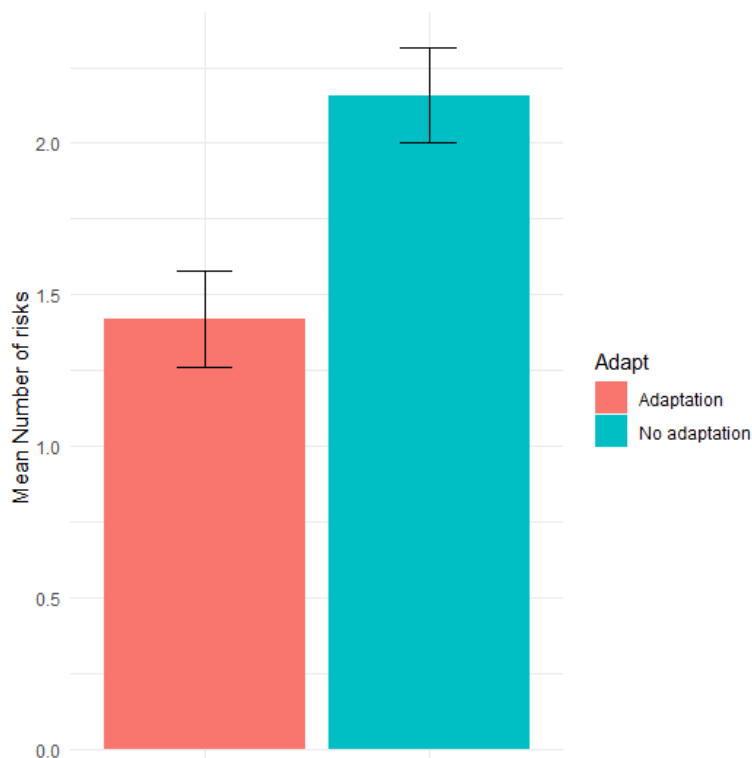


Figure 10. Means of the number of risk exposure in the condition adaptation and no adaptation.

3.4. H3: There is an interaction between the effect of the degree of cobot adaptation and the effect of the expertise of the participant.

To test an interaction effect, there need to be two significant single effects: this is the case for the "risk exposure" dependent variable. Both the expertise of the participant and the adaptation of the cobot have an effect on risk exposure.

A generalized repeated-measures mixed model was run to test for an interaction effect. No interaction effect was found, the adaptation of the cobot does not moderate the effect of the expertise in terms of errors ($F(1)=0,7896;p=0,380479$).

4. Discussion

4.1. On the effect of expertise

This study aimed to provide an innovative proof of concept on the impact of human/cobot collaboration in a risky work situation. Indeed, we tested the effect of the participant's expertise (expert vs non-expert) on performance, workload, acceptability and risk taking. There was no effect of the expertise on the workload. Expert participants did less errors than non-expert. The training session seemed to have succeeded in making them experts. However, everyone succeeded in the task, whatever their level of expertise. Which means that, in both conditions, the cobot deals with the interindividual variability of the expertise by providing help to assemble the figure. However, there was no effect of the level of expertise on the acceptability scores. This result is contrary to what our colleagues, Cippelletti et al. (2017), have found. This means that the cobot is not a hindrance to the experts, unlike in Cippelletti et al. (2017) situation, where the software was not useful, hindered the experts more than the novices, and required them to perform additional tasks. The level of expertise had an impact of the risk taking. Expert participants took less risks than non-experts with or without the cobot. There may be an effect of learning the figure. This could mean that a human/cobot duo will allow the human to expose himself to less risks to realize a task in collaboration. However, this study is only a proof of concept, designed in a laboratory setting, therefore, results have to be taken with caution.

4.2. On the effect of adaptation

The experimental setup enabled the comparison between a collaboration in which the cobot adapts to the operator safety constraints and one in which it does not adapt. This technical variability could impact the operator and his task. To the best of our knowledge, this comparison has never been tested before. Experiments usually compare two types of collaboration, according to the actors of this collaboration (Fournier et al., 2022, 2024), and according to the level of adaptation to human variability (Hiatt et al., 2011; Peternel et al., 2018). Only one study has tested the impact of a cobotic collaboration on performance, workload and posture in the presence of a technical variability, the pace imposed by the cobot (Bouillet et al., 2023). In our case, the adaptation had no effect on the perceived acceptability. Participants had positive perceptions toward the cobot whether it adapted or not. There was no effect either on the number of errors and on the success of the task. However, the adaptation of the cobot to the safety constraints of the human had a positive impact on the number of risk exposures by participants. Indeed, in the condition of adaptation, participants expose themselves to less risks (aka: touch the red blocks) and when they did, it was when there was no other solution (at the very end of the assembly if the cobot had no block left). The cobotic solution we have designed enables the operator to expose themselves to fewer risks, and to do so spontaneously. Those results could inspire future studies that could validate the benefits of implementing a cobotic system in workstations exposed to risks.

4.3. Limits

In future studies, it could be interesting to enable participants to work in longer time periods with the cobot. This would enable us to point the medium to long time impact of a cobotic collaboration on the performance and the acceptability of the human. Also, having more participants, including participants that have already worked with a cobot is important for

statistical analysis. Indeed, the influence of real experts of the industry could have a very different impact on the results found. In the experiment, the participants were all from an academic background, which may introduce a sampling bias. Therefore, the results should be interpreted with caution. Unfortunately, the experiment was impacted by numerous cobot bugs which may have affected the results, even though we tested their impacts and found none. And, certain dimensions, such as the acceptability of the cobotic collaboration, were measured through indirect measures (e.g. auto-reported questionnaire). Future studies could increase the generalizability of results by using more direct measures. To conclude on the limits, researchers should focus on other dimensions of the user experience to understand all aspects of work transformation when introducing a cobotic collaboration. Indeed, there needs to be studies on the long-term effects, such as impeded or facilitated work (Bobillier Chaumon, 2016).

4.4. Practical implications

There are obvious practical implications to those results. However, this is a laboratory experiment, so those implications have to be treated with caution. Firstly, there seems to be no issues to implement a cobotic collaboration with experts as their level of acceptability stays high. Secondly, it is possible to make a cobotic system consider human safety constraints by adding a high cost to a specific dangerous action. This adaptation reduces the human exposure to risks and does not negatively impact the quality of the task. And lastly, non-experts can succeed in a difficult task as well as the experts with the help of a cobot.

5. Conclusion

This research is a laboratory experiment testing the effect of the level of human expertise and the level of adaptation of a cobotic system to human safety constraints on the performance (success of the task and number of errors), the workload, the number of risk exposures and the acceptability during an industrial-like assembly task. The results suggest that it may be possible

to adapt a cobotic solution to human safety constraints without apparent negative impact on performance, workload, or the acceptability of collaboration. It suggests that cobots could assist humans in supporting high-risk operations. However, these findings are exploratory and originate from a proof of concept. There needs to be further analysis to validate these observations. Cobotic solutions and work designers could draw inspiration from our results to support the design of constraints in workstations for high-risk work operations.

6. Contributions

Étienne Fournier: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Supervision, Visualization, Writing – original draft, revisions of the draft

Aurélie Landry: Conceptualization, Funding acquisition, Methodology, Project administration, Resources, Supervision, Validation, Writing – review and editing

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ACCEPTED