International Journal of Industrial Ergonomics 87 (2022) 103241

Contents lists available at ScienceDirect

International Journal of Industrial Ergonomics

journal homepage: www.elsevier.com/locate/ergon

Fostering short-term human anticipatory behavior in human-robot collaboration

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A R T I C L E I N F O

Keywords:
Human-robot collaboration
Anticipatory behavior
Adaptive behavior
Visual cues

A B S T R A C T

The present study reports on a human-robot collaboration experiment involving an industrial task with the specific aim of exploring the effects of (i) fostering human anticipatory behavior towards the robot, through visual cues of the robot's next move and (ii) robot adaptiveness to the human actions through reducing its motion speed with respect to human movement's proximity. For investigating these effects a generic collaborative picking and sorting task was designed, implemented and tested by volunteer participants, in a Virtual Reality simulation environment. Results demonstrated that, showing robot's intent through anticipatory cues significantly increased team efficiency, human safety and collaborative fluency in conjunction with a positive subjective inclination towards the robot. Robot adaptiveness significantly increased human safety without decreasing task efficiency and fluency, compared to a control condition.

1. Introduction

We face an era of a new "Industrial Revolution" in robotics. Artificial Intelligence (AI) is growing rapidly and promises to make robots a part of our everyday life. With the continuous advances of technology, robots are becoming even more flexible and adaptive in the environment, as well as increasingly capable of working along with human operators in production facilities. In the near future, robots are expected to alter the nature of the traditional work process allocation between humans and machines (Hancock et al., 2013). The primary goal of Human Robot Interaction (HRI) research is to ensure safety and maximize performance, dependability, resilience and robustness in mixed Human Robot (HR) environments (Bartneck et al., 2020; Feil-Seifer and Matarić, 2009; Goodrich and Schultz, 2007; Tsarouchi et al., 2016). Until recently, the best practice to ensure human safety during an interaction with a robot, especially in an industrial context, was a minimum separation distance between them (Helander, 1990; Kulić and Croft, 2006; Zurada et al., 2001). However, even though this practice ensures operators' safety, it negatively affects efficiency, due to the fact that robots occupy large spaces and their operation must be ceased when the human approaches in order to perform his task. This emerging need to increase human-robot team's efficiency has led to the physical cooperation between humans and robots, often sharing a common space. Broadly speaking, HRI can be divided into three main categories (Bauer et al., 2016; International Organization for Standardization, 2016; 2011; Schmidtler et al., 2015):

- Coexistence – where human and robot work alongside each other but do not share a workspace.
- Cooperation – where human and robot work at the same time in the shared workspace, but they do not work simultaneously on the same product or component.
- Collaboration – where human and robot work simultaneously on the same product or component.

Recently, researchers have focused their attention to the last category, a rapidly increasing sub-domain of HRI the Human-Robot Collaboration (HRC) (Matsas et al., 2013; Maurice et al., 2017; Michalos et al., 2015; Villani et al., 2018). Undoubtedly, significant benefits may come from such combination of human's cognitive skills, such as contextual flexibility, problem solving and dexterity, with the robot's advantages such as speed, repeatability, power and precision. However, collaboration between heterogeneous agents poses significant challenges. Generally, "collaboration occurs when a group of autonomous stakeholders of a problem domain engage in an interactive process, using shared rules, norms, and structures, to act or decide on issues related to that domain" (Wood and Gray, 1991). In HRC, this includes sharing a common workspace, working under common rules, sharing common plans and goals, and seamlessly understanding each other. Therefore, for successful collaboration to occur, both agents, human and

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https://doi.org/10.1016/j.ergon.2021.103241
Received 8 June 2021; Received in revised form 28 September 2021; Accepted 16 November 2021
Available online 25 November 2021

robot, should be able to perceive and accommodate their behavior to their collaborator. Since humans unavoidably exhibit dynamic behaviors, an AI-enabled robot should be able to dynamically alter its behavior in the course of collaboration to adapt to the human. Indeed, robot adaptive behavior has been shown to positively affect task efficiency (Huang et al., 2015; Huang and Mutlu, 2016; Lasota and Shah, 2015). However, besides efficiency, maintaining safety is also essential. Although robot adaptiveness may indeed contribute to safety by predicting human motions, it may also negatively affect it in certain cases by making the robot's movements more obscure to the human.

Achieving maximum levels in both these goals is often challenging; frequently while trying to maximize one of them a cutback might occur to the other one. For example, as mentioned above an easy and effective way to ensure safety is ceasing robot motion while human is in close proximity. Nonetheless, these recurrent stops inevitably result in an increase of task completion time, thus negatively affecting efficiency. Consequently, a critical challenge for designers of collaborative robotic systems is how to reduce the tradeoff between these two criteria to arrive in more seamless collaboration. Seamlessness of collaboration is generally examined through the notion of fluency. Fluency can be defined as a collaborative system's level of internal efficiency regarding use of its resources. It designates that the cooperation and agents' actions are harmonized with each other, resulting in minimization of the coworkers' waiting times and consequently in improvement of the overall team performance (Entin and Serfaty, 1999; Gombolay et al., 2015; Hoffman, 2019; Hoffman and Breazeal, 2010). In other words, fluency evaluates the influence of a design choice on collaboration per-se, rather than the objective measure of task efficiency, which can be influenced by other factors related to task environment. Although there is no universal measure for evaluating fluency in collaboration, typical metrics used include agents' idle time, agents' concurrent action time, and subjective ratings (Cakmak et al., 2011; Dragan et al., 2015; Hoffman, 2019; Hoffman and Breazeal, 2007; Lasota and Shah, 2015; Nikolaidis and Shah, 2013; Thomaz and Chao, 2011).

Every fluent collaborative task depends on mutual anticipation, since its agents, in addition to the normative action sequence, are supposed to possess circumstantial knowledge of their partners' upcoming moves for effective coordination. In fact, planning ahead and responding preemptively greatly improves cooperation between the agents (Breazeal et al., 2005; Matsas et al., 2018; Pandey et al., 2011; Sebanz et al., 2006). As Klein et al. (2004) point out "*To be a team player, an intelligent agent must be reasonably predictable and reasonably able to predict others' actions*". Likewise in HRC, each intelligent collaborating agent should possess an internal behavioral model of itself and its collaborator along with a forecasting mechanism of the future actions related to the collaborative task (Bubic et al., 2010; Butz et al., 2003).

Several studies have demonstrated the beneficial effects of anticipatory behavior in HRI, i.e. improvement of team efficiency, coordination and fluency, as well as humans' perceived satisfaction of collaboration. However, most of these studies adopt a robot-centered approach, focusing on enhancing robot anticipatory behavior towards human's actions. For example, Cui et al. (2019), Hoffman and Breazeal (2010), Iqbal et al. (2016) and Ji et al. (2020) showed that robot anticipatory behavior not only improves team performance, but also results in a more natural and fluent interaction. Furthermore, Hoffman and Breazeal (2007) reported that anticipatory robot decisions, based on the confidence of their validity and their relative risk, significantly improved the best-case task efficiency as well as human's perception of robot's commitment to the team. Robots use various inferences to predict human intents and movements such as exploitation of data taken from sensors (Buerkle et al., 2021; Kanda et al., 2008; Koppula and Saxena, 2016; Kratzer et al., 2020; Liu and Wang, 2018; Sakita et al., 2004), implementing techniques and dynamic models of the interaction history (Dominey et al., 2008; Gui et al., 2018), control algorithms (Fishman et al., 2020; Mainprice et al., 2015), and cost/reward-based frameworks (Hoffman and Breazeal, 2007; Nikolaidis et al., 2015).

On the other hand, studies dealing with the human-centered perspective, i.e. human anticipation and predictability of robots' future moves are limited. Until recently, HRC researchers mainly focused their attention of fostering human's abilities as a collaborator, through training (Freedy et al., 2007; Lin et al., 2002; Matsas and Vosniakos, 2017; Nathanael et al., 2016b). However, an effective way to achieve successful HRC while reducing the aforementioned efficiency – safety tradeoff may involve interaction cues similar to the ones observed in Human – Human (H–H) collaboration. A small number of studies have examined techniques for communicating robot intent to the human collaborator; these include gestures (Gielniak and Thomaz, 2011; Lohse et al., 2014), verbal cues (St. Clair and Mataric, 2015), gazes (Boucher et al., 2012; Huang and Mutlu, 2012; Lallee et al., 2013), projected visual cues (Ganesan et al., 2018), and legible or expressive actions (Dragan et al., 2013, 2015; Stulp et al., 2015; Takayama et al., 2011). The aforementioned studies provide some evidence regarding the benefits of fostering human anticipatory behavior into HRI.

Regardless of the sensory channel used (e.g. auditory or visual), it can be argued that conveying information between robot and human in a collaborative task can be classified according to the illocutionary acts from Searle (1976) Speech Act theory, according to which when a speaker makes an utterance, he/she intends to express an attitude with a certain function or "force," to the listener. Hence, based on this theory, at least three distinctive modes of human-robot communication can be identified: (i) assertives, where a collaborative agent can either refer to the present state of affairs or to the future course of action, (ii) directives, where a collaborative agent requests its collaborator to perform an action, and (iii) commissives, where a collaborative agent expresses its own intent.

The simplest way for a robot to convey information to the human is by assertives i.e. by providing feedback on the current status/state of affairs. Such feedback helps the human to learn faster how to coordinate with the robot, since through robot responses he/she understands what went right or wrong. Different kinds of techniques have been used for implementing such assertives varying from visual boundaries of working envelope along with movement alert (Matsas et al., 2018; Michalos et al., 2016), to expressive robot's lights (Baraka et al., 2016), text-based information (El Makrini et al., 2017), and gestures (Sauer et al., 2021).

Also, a number of studies using mainly humanoid robots have showed that implicit cues coinciding with directives, such as robots' gaze behaviors (Boucher et al., 2012; Huang and Mutlu, 2012; Lallee et al., 2013), deictic gestures (Lohse et al., 2014) and visual cues (Ganesan et al., 2018), facilitate HRC collaboration.

To our knowledge, there are few studies explicitly dealing with commissives, i.e. expression of robots intent. Takayama et al. (2011) argued that showing forethought through expressions that communicated what the robot was planning to do, can improve robot's readability. In their experiment, participants viewed animated clips of a robot trying to accomplish a variety of tasks, either with or without forethought, and then asked to interpret its actions. The authors concluded that showing forethought helps people to ascertain their interpretations of the robot imminent behavior, and therefore increases people's confidence and willingness to engage in interaction with these robots as the robot seem more appealing and approachable. In the same vein, Dragan et al. (2015) demonstrated that legible, namely easily readable, robot motion greatly improves interaction efficiency and positive evaluation of the robot. In their experiment participants collaborated with a robot to fulfill certain tea orders in a coffee shop scenario. The authors compared three types of robot motion: functional (optimizing goal trajectory and avoiding collisions), predictable (matching what the collaborator would expect, given the known goal), and legible (helping the collaborator to infer the goal through exaggeration in robot end effector trajectory). Even though legible motion required a longer trajectory it resulted in increased efficiency compared to the so called predictable motion, as participants inferred the robots goal earlier and even more so compared to the functional motion where participants had difficulty in coordinating with the robot, leading in a steep increase of task completion time.

The current study aims to explore how human anticipatory behavior or robot adaptiveness affect joint Human - Robot task efficiency, fluency and safety in an industrial HRC task. Specifically, it aims to explore the effects of (i) robot's visual commissive cues on fostering human anticipatory behavior and (ii) to compare the latter method with a more widely studied alternative in the form of robot adaptiveness (i.e. prevention mechanism) to human actions.

To this end, visual cues of the robot's next move were implemented in the experimental task environment and were presented to the human as means of enhancing his anticipatory behavior. In addition, a rudimentary robot prevention mechanism was implemented and examined as an alternative means of enhancing collaboration, where the robot adapts its motion speed with respect to human movement's proximity. Two hypotheses are respectively investigated:

H1. Reducing the robot's movement speed while in close proximity with the human will increase safety; but is expected to have a negative effect on task efficiency.

H2. Not reducing the robot's movement speed, but providing the human with a visual cue of the next move the robot is about to take will increase task efficiency along with safety and collaborative fluency.

For studying these effects an appropriate task was designed and tested by volunteer participants in a Virtual Reality simulation environment created in Unity 3D™ along with a human arm motion tracking system developed in house by the NTUA Ergonomics Lab. The remainder of the paper is structured as follows: in the following section the task environment, the experimental design and the procedure are described, followed by the results and discussion sections.

2. Methodology

2.1. Task design

To evaluate the aforementioned hypotheses, an HRC task was designed in a Virtual Environment (VE). Virtual Reality (VR) was preferred to simulate the testing environment due to the numerous benefits it offers, such as cost effectiveness (a real robot is not required), the absence of risk to humans (potentially harmful real collision with the robotic arm is avoided), immersiveness, accuracy, reduced task completion times and increased user situation awareness (Cobb et al., 1995; de Giorgio et al., 2017; Dimitrokalli et al., 2020; Malik et al., 2020; Nathanael et al., 2016a; Or et al., 2009; Oyekan et al., 2019; Rückert et al., 2018; Tang et al., 2019). However, a downside of VR is that a virtual robot may distort the perceived feeling of safety and thus may drive users in taking more risks than when collaborating with an actual robot in an industrial cell.

The design of such a task, presents several challenges. Specifically, the task should be engaging, similar to real life applications, evoke a sense of collaboration, collision understanding, and most importantly be relatively quick to finish to minimize dizziness caused by the long use of head-mounted display (Lin et al., 2019; Serge and Moss, 2015; Wu et al., 2020). On the other hand, it should not be too short in duration in order to allow for an adequate amount of data to be collected. Furthermore, it should be complex enough to support the formation of tradeoffs between task efficiency and safety, in conjunction with interesting collaborative behaviors.

To this end an industrial picking and sorting task, which may form part of an assembly line, was conceived. This task may be rather generic, however it constitutes a base for a wide range of industrial tasks, like mixed assembly and packaging tasks, where the robot is responsible for the heavier parts, or quality control tasks where human's visual perceptual acuity along with robot's scan vision results in capacity increase. It should be noted that due to the inherent difficulty in implementing a VR task with genuine concurrent manipulation of the same workpiece (i.e. absence of proper tactile feedback) the collaborative task was designed without concurrent Human Robot manipulation but nevertheless requiring constant coordination between the two agents.

In detail, the designed task involved picking thirty-six balls from a table and positioning them to a conveyor belt leading to a storage basket. The human participant was in a seated posture and had to collaborate with the robot by sharing the ball picking task with it (see Fig. 1). Balls were dynamically assigned to the human by, turning green prior to being picked (see Fig. 2). The pre-assignment of balls was explicitly designed as to induce possible collisions between the human and the robot. Several testing iterations were conducted for choosing adequate parameters such as robot speed (i.e. in compliance with ISO/TS 15066 safety requirements, but not too slow and unchallenging for the human participant), distance between picking balls (i.e. not too close with each other for avoiding colliders meshing, but not too far in order to promote common human-robot workspace), picking sequence (so as to encourage mingling of human and robot arm trajectories), distance threshold for decreasing robot speed (i.e. enough to allow for participant reaction, but not too high by virtue of task efficiency), and so on. In addition enhancing the feeling of collaboration was particularly important. However, during pilot testing it was observed that most pilot users experienced the task as being rather competitive than collaborative. Typical accompanying comments were "I pick up my objects and the robot picks up its own" and "I need to finish first before the robot does". In order to rectify this feeling of competition, the task pacing was

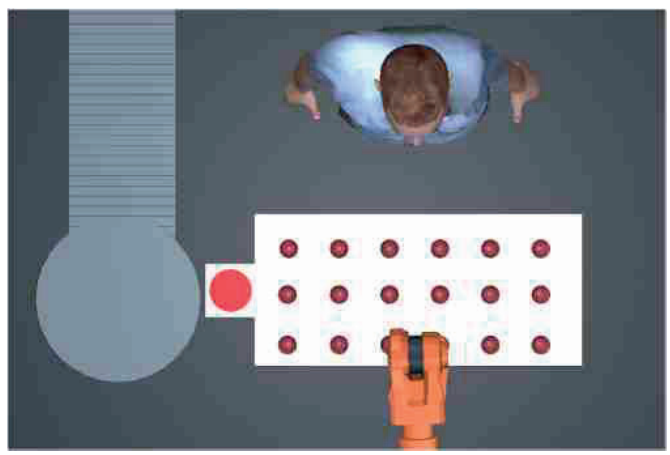

Fig. 1. Setup of the Virtual Collaborating task.

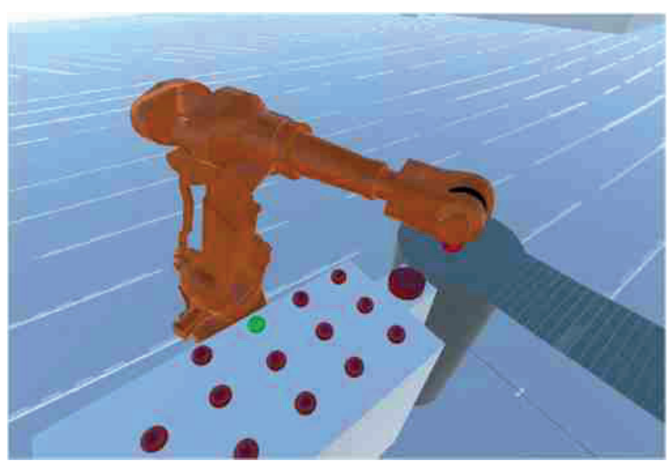

Fig. 2. Green color indicates the ball to be picked by the participant. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

explicitly altered in the final design so that the human agent controlled the pacing of the process, meaning that the robot followed the human without being able to surpass him/her. This pacing alteration fully remedied the above issue. In fact, similar task sequence restrictions can be found in industrial assembly tasks where placement of certain components requires other ones to be placed previously by the collaborating agent, or in a welding task where wielding cannot start before the pieces are placed in the correct positions. Furthermore in case of a collision the robot retreated to a safe position and the participant had to press a button to resume the process. The robot was set to return to its initial position after placing a ball to the conveyor belt, before picking its next ball. To increase task duration and to give a sense of task continuity, two sets of trays with balls were manipulated, each containing 18 balls.

2.2. Apparatus

All participants were equipped with a wearable motion tracking system enabling them to manipulate their virtual avatar. A head-mounted display (HMD) was used as a stereoscopic visual display and a GoPro camera for experiment recording. A simplified overview of our system is depicted in Fig. 3.

To monitor the movement of the human arm, a motion tracking system was used, capable of tracking from the shoulder up to the hand palm (Mourelatos et al., 2019). The wearable system consisted of three MPU 9250 IMUs connected to an Arduino Nano with 24AWG wires and mounted on a fingerless glove and elbow patch. Although various systems implementing arm tracking in VR already exist, the system in question retains certain benefits not found in existing systems. The main advantage it provides is that it can function independently from any type of position tracking technology or display, rendering it entirely portable. A picture of the arm mount of the current motion tracking system is shown in Fig. 4.

The Oculus Rift DK2 Virtual Reality HMD was used as a display. Oculus Rift provides high resolution of 1920 x 1080 and a 100° total Field of View increasing the immersion of the participant. A sensor camera allows the tracking of head movements of the participant in real time, at a rate of 60 fps letting him/her observe the whole scene constantly. For the purposes of this study, it was decided to deactivate the leaning tracking sensor in order to reduce motion sickness.

The development of the VE was made with the cross-platform game engine Unity 3D™. Unity is a complete 3D modeling tool that gives users the ability to create highly realistic games and experiences in both 2D and 3D. The simulated HRC scenario took place in a virtual industrial hangar. The virtual collaborating robot was the ABB IRB 6600 industrial robot and was positioned to the opposite side of the table facing the participant. Robot's moving speed complied with ISO/TS 15066 safety requirements.

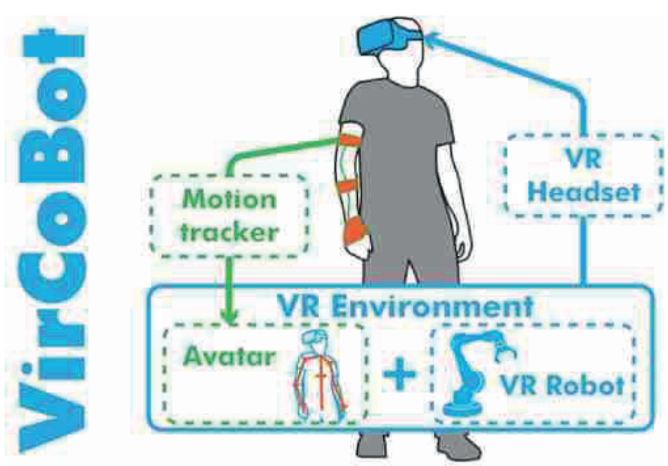

Fig. 3. Overview of the technical system.

Fig. 4. Arm mount of the current motion tracking system.

2.3. Participants

A total of 48 volunteers participated in the experiment (33 males, 15 females) all mechanical engineering students at the National Technical University of Athens, with ages ranging from 20 to 31 (M = 24.5, SD = 2.5). Only 25% of the participants had prior experience in VR simulation. Recruitment of participants and data collection was conducted in accordance with National Technical University of Athens ethics procedures concerning research involving human participants. Also, all participants provided informed consent before the trials.

2.4. Experimental design

In order to compare the effect of robot anticipatory cues and of robot adaptiveness on the simulated HRC task, a within subjects experimental design was selected with robot mode as independent variable and three conditions i.e. Anticipation (A), Prevention (P) and Control (C). The within-subjects design was selected in order to reduce bias associated with individual differences. The order of the conditions was fully compensated to avoid learning and order effect (resulting into six possible order sequences i.e. APC, ACP, PAC, PCA, CAP, and CPA, each assigned to eight participants, adding to a total sample size of 48). Therefore, each participant completed the designed task in all three conditions:

1. "Anticipation" condition, where the next ball the robot was about to pick was highlighted with a different color (see Fig. 5). With this indication the human was able to perceive robot's planning phase and anticipate its next move. Coloring the ball was preferred as an explicit cue since it bears necessary information, still without increasing human mental workload. Similar technological solutions

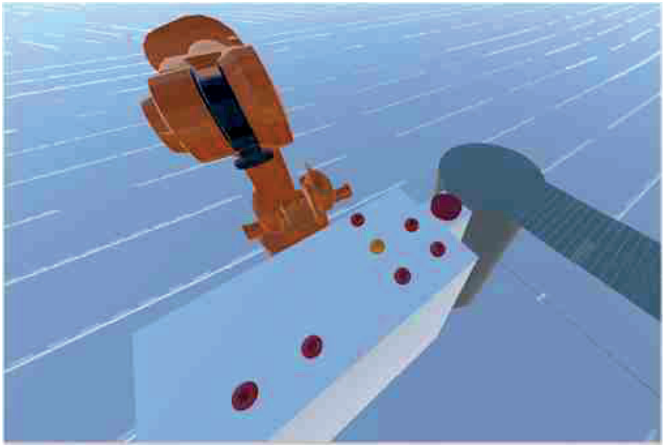

Fig. 5. Orange color indicates the next ball the robot is about to pick. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

have also been implemented in previous studies in Augmented Reality environments (Ruffaldi et al., 2016) and in mixed-reality ones (Ganesan et al., 2018).

2. “Prevention” condition, where an adaptive “slow down” function was implemented to the robot. “Slow down” function was triggered when the robot detected that the proximity between the virtual human hand and any part of the robotic arm and end effector was less than 20 cm. In this mode the robot reduces its speed –to 50% of the original-in order to possibly prevent collision with the human by increasing the time interval the human has to react. Reduced speed is maintained as long as proximity remains less than 20 cm, otherwise robot’s speed reverts to its original value. Robot slowdown values for proximity and speed reduction were chosen after several trials to allow for preventive reaction without overly hindering task flow.
3. “Control” condition, where the robot functions independently of human movement and without cues of its next move.

The Task Completion Time and the Number of Collisions during each condition and set of trays (1st, 2nd) were recorded, analyzed and used to measure overall task performance and safety respectively. In addition, Human Idle Time, i.e. the percentage of the total task time that the human was not active, was measured to assess collaboration fluency. A description for each dependent variable follows below.

2.4.1. Number of Collisions

Refers to collisions that occurred during collaboration, i.e. during the concurrent motion of human and robot. It includes: i) *Total Collisions:* the sum of collisions that occurred during both set of balls, ii) 1st *Set Collisions*, and iii) *2nd Set Collisions*.

2.4.2. Task Completion Time

Refers to time spent for both human and the robot to collect their balls. It includes: i) *Total Completion Time:* the overall time spent until the completion of the task, ii) 1st *Set Completion Time* and iii) *2nd Set Completion Time*.

2.4.3. Human Idle Time

Refers to the time the human was idle during the collaboration task, meaning that he/she was not active. Human Idle Time can be separated in (i) the amount of time the human is waiting for the robot to move, on the flow of the collaboration, and (ii) the amount of time the human has finished his/her part of the task and is waiting for the robot to accomplish its part. This partition was selected due to the slight difference of their meaning. The first one is considered the most important, as it is directly linked with collaboration fluency. The more uncertain and unsafe the human feels about the robot’s motion, the more time he/she spends waiting for it, thus negatively affecting collaboration fluency. On the other hand, the second one implicitly reveals fluency through the number of the remaining balls that the robot has to collect because it was left behind. For the purposes of this research only the first one is reported. Therefore, Human Idle Time metric includes: i) *Human Idle Time during Collaboration:* the total time human was idle while the robot was moving, ii) *1st Set Human Idle Time during Collaboration* and iii) *2nd Set Human Idle Time during Collaboration*.

2.5. Questionnaire

Along with the objective measures, a subjective evaluation was conducted through a self-administered questionnaire right after completion of the experiment. The questionnaire solicited participants’ demographic information (including age, gender, etc.) and their overall VR experience regarding HMD sickness, movement naturalness, immersiveness of the environment, collision awareness and the perceived feeling of collaboration from the robot in each condition. All questions were in five point Likert scale, where 1 stands for full disagreement with the statement and 5 stands for full agreement (Table 4). In addition, there was a single three level question regarding users’ preference of condition in terms of perceived safety (Table 5). The questionnaire was designed so as to avoid acquiescence bias (i.e. statements seeking agreement were avoided, questions were neutral, did not require prior knowledge and participants were instructed to answer only based on their specific VR trial experience).

2.6. Experimental procedure

Before the trials participants were informed about the desirable goal, i.e. to collaborate with the robot in order to collect and place all the balls from the table aside to a conveyor belt as quickly as possible, still under the umbrella of safety. Participants were explicitly instructed to create and follow their own desired strategy for goal achievement, taking though into consideration both avoiding a collision with the robot and faster task accomplishment. Next, participants were seated in front of a table and completed a practice tutorial for familiarization with the VE and the movement of their virtual hand. In the beginning of each trial the experimenter provided additional information about the robot mode condition (i.e. Anticipation, Prevention or Control) and the wearable tracking system along with the HMD were donned to them. For better results a calibration of the wearable tracking system’s sensors before each condition was performed. All participants were asked to answer a post-experiment questionnaire right after the experiment.

In Fig. 6 a participant run with the final configuration is presented.

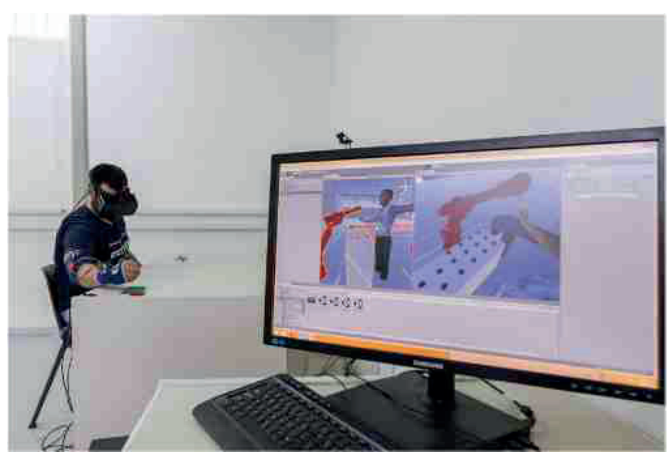

Fig. 6. Experimental setup where the participant executes the collaborative task (left) while the virtual simulation is shown in real time (right).

All experimental trials were also recorded with an external camera for post analysis and checking for any procedure violations.

3. Results

The accumulated data were analyzed in IBM SPSS Statistics (version 26). Three outliers were excluded after boxplot inspection. Normality of the data was assessed using the Kolmogorov-Smirnov normality test and was verified for Task Completion Time and Human Idle Time. A one-way repeated measures analysis of variance (ANOVA) with 3 levels (Control, Prevention, and Anticipation) was conducted on these two dependent measures along with Mauchly's Test of Sphericity. Partial eta-squared (η_p^2) was used as a measure of effect size. The non-parametric Friedman test was used for the Number of Collisions along with post hoc Wilcoxon signed-rank test, since the normality assumption was violated. Bonferroni corrections were applied in all three dependent measures for multiple comparisons.

Analysis of the measurements metrics were examined first as total and then divided in the two sets of balls (1st set, 2nd set) in order to investigate if learning effects within each condition affected performance. Overall data charts are presented in Fig. 7.

3.1. Number of Collisions

3.1.1. Total Collisions

There was a statistically significant difference in the Number of Collisions that occurred during trials (χ^2 (2) = 17.354, $p < .001$) (Table 1). Post hoc analysis resulted in a significance level set at $p < .017$ and showed that participants made significantly fewer collisions in the Anticipation condition and in the Prevention condition compared to the Control condition (Z = −4.008, $p < .001$ and Z = - 2.940, p = .003 respectively). The difference between the first two conditions did not reach significance (Z = −1.563, p = .118).

3.1.2. 1st Set Collisions

There was a statistically significant difference in the Number of Collisions that occurred in the first set (χ^2 (2) = 6.183, p = .045) (Table 1). Post hoc analysis resulted in a significance level set at $p < .017$ and showed that participants made significantly fewer collisions with the robot in the Anticipation condition compared to the Control condition (Z = −2.648, p = .008). On the other hand, Prevention condition did not reach significance with either Anticipation or Control conditions (Z = −0.881, p = .378 and Z = −1.850, p = .064 respectively).

3.1.3. 2nd Set Collisions

There was a statistically significant difference in the Number of Collisions that occurred during trials (χ^2 (2) = 23.928, $p < .001$) (Table 1). Post hoc analysis resulted in a significance level set at $p < .017$ and showed that participants made significantly fewer collisions in the Anticipation condition and in the Prevention condition compared to the Control condition (Z = −4.124, $p < .001$ and Z = - 3.314, p = .001 respectively). The difference between the first two conditions did not reach significance (Z = −2.148, p = .032).

3.2. Task Completion Time

3.2.1. Total Task Completion Time

There was a significant main effect of robot mode on Total Task Completion Time (F (2, 88) = 12.205, $p < .001$, $\eta_p^2 = 0.217$) (Table 2). Post hoc tests showed that the task was finished significantly earlier in the Anticipation condition compared to both Prevention ($p < .001$) and Control (p = .001) conditions. However, the difference between these

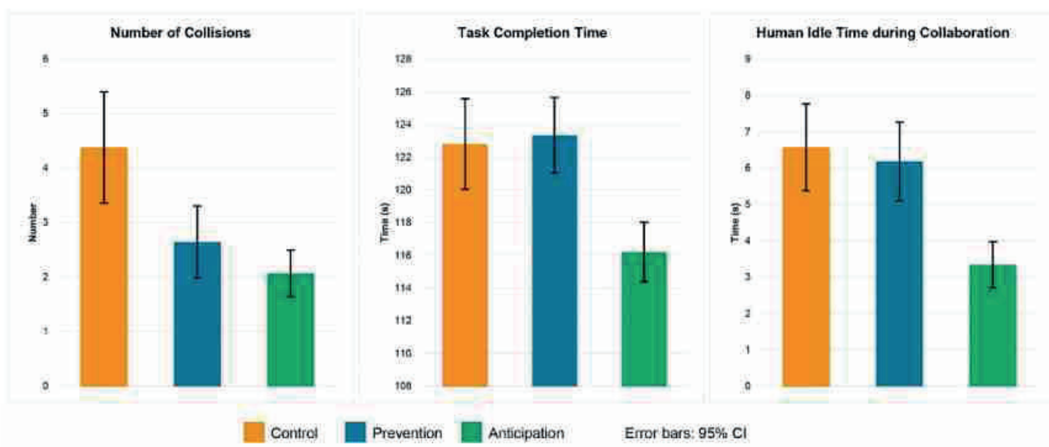

Fig. 7. Mean values, with error bars representing the 95% confidence interval (CI) of a mean, of Number of Collisions (left), Task Completion Time (middle), and Human Idle Time during Collaboration (right) for Control, Prevention and Anticipation conditions for the total task.

Table 1
Number of Collisions

	Control		Prevention		Anticipation				
	M	SD	M	SD	M	SD	χ^2	df	p
1st set	2.38	2.12	1.66	1.55	1.38	1.14	6.183	2	.045
2nd set	2.00	1.69	0.98	1.05	0.69	0.82	23.928	2	<.001
Total	4.38	3.40	2.64	2.20	2.07	1.42	17.354	2	<.001

Table 2
Task Completion Time

	Control		Prevention		Anticipation				
	M	SD	M	SD	M	SD	F	η_p^2	p
1st set	61.04	7.17	61.07	5.40	57.51	4.98	5.059	.103	.011
2nd set	61.76	4.88	62.26	4.69	58.69	3.85	10.439	.192	<.001
Total	122.80	9.23	123.33	7.69	116.20	6.06	12.205	.217	<.001

latter two conditions did not reach significance ($p > .05$).

3.2.2. 1st Set Completion Time

There was a significant main effect of robot mode used on Task Completion Time (F (1.76, 77.46) = 5.059, $p = .011$, $\eta_p^2 = 0.103$) (Table 2). Post hoc tests showed that 1st set was finished significantly earlier in the Anticipation condition compared to both Prevention ($p = .004$) and Control ($p = .029$) conditions. However, the difference between these latter two conditions did not reach significance ($p > .05$).

3.2.3. 2nd Set Completion Time

There was a significant main effect of robot mode on Task Completion Time (F (2, 88) = 10.439, $p < .001$, $\eta_p^2 = 0.192$) (Table 2). Post hoc tests showed that 2nd set was finished significantly earlier in the Anticipation condition compared to both Prevention ($p < .001$) and Control ($p = .004$) conditions. However, the difference between these latter two conditions did not reach significance ($p > .05$).

3.3. Human Idle Time

3.3.1. Total Human Idle Time during collaboration

There was a significant main effect of robot mode on Total Human Idle Time (F (2, 88) = 26.064, $p < .001$, $\eta_p^2 = 0.372$) (Table 3). Post hoc tests showed that participants spent significantly less time being idle in the Anticipation condition compared to both Prevention ($p < .001$) and Control ($p < .001$) conditions. However, the difference between these latter two conditions did not reach significance ($p > .05$).

3.3.2. 1st set Human Idle Time during collaboration

There was a significant main effect of robot mode on Human Idle Time in the 1st set (F (2, 88) = 18.263, $p < .001$, $\eta_p^2 = 0.293$) (Table 3). Post hoc tests showed that participants spent significantly less time being idle in the Anticipation condition compared to both Prevention ($p < .001$) and Control ($p < .001$) conditions. However, the difference between these latter two conditions did not reach significance ($p > .05$).

3.3.3. 2nd set Human Idle Time during collaboration

There was a significant main effect of robot mode on Human Idle Time in the 2nd set (F (2, 88) = 9.770, $p < .001$, $\eta_p^2 = 0.182$) (Table 3). Post hoc tests showed that participants spent significantly less time being idle in the Anticipation condition compared to both Prevention $p = .002$) and Control ($p < .001$) conditions. However, the difference between these latter two conditions did not reach significance ($p > .05$).

3.4. Subjective evaluation

Questions and results of the self-administered post-experiment questionnaire are presented below.

With respect to VR task design and experience user opinion was overall positive (Table 4). 90% of participants reported immersion in the VE (Q.1) while only 25% did not feel like grabbing the physical ball (Q.2). Moreover, only 6% experienced some difficulty in hand movement (Q.3) whereas 17% felt that their hand movement was not natural (Q.4). Regarding collision awareness, 92% acknowledged the collision with the robot (Q.5). Furthermore, almost everyone, i.e. 98% did not feel any discomfort during trial (Q.7) and only 21% of the participants

Table 3
Human Idle Time

	Control		Prevention		Anticipation				
	M	SD	M	SD	M	SD	F	η_p^2	p
1st set	3.33	2.31	2.90	2.23	1.44	1.19	18.263	.293	<.001
2nd set	3.25	2.11	3.28	2.31	1.90	1.49	9.770	.182	<.001
Total	6.57	3.97	6.18	3.60	3.34	2.11	26.064	.372	<.001

Table 4
Questionnaire results (SD: strongly disagree, D: disagree, N: neutral, A: agree, SA: strongly agree, f: frequency).

	Question	SD		D		N		A		SA	
		f	%	f	%	f	%	f	%	f	%
1.	I felt like I was inside the simulation environment	1	2	1	2	3	6	25	52	18	38
2.	I felt like I was actually catching a ball, even though the ball had no physical mass	5	10	7	15	14	29	20	42	2	4
3.	My hand movement in the VR environment was restricted	16	33	19	40	10	21	2	4	1	2
4.	I could move my hand in the VR environment naturally	0	0	8	17	19	40	16	33	5	10
5.	I was aware when there was a collision with the robot	2	4	1	2	1	2	15	31	29	61
6.	I felt that the robot was collaborating with me to accomplish the task	3	6	7	15	13	27	15	31	10	21
7.	During the experiment I felt dizziness or any other discomfort	40	83	7	15	0	0	1	2	0	0

Table 5
Subjective condition preference (f: frequency).

Question	Control		Prevention		Anticipation	
	f	%	f	%	f	%
In which of the three conditions would you feel safer in a real shared workplace?	0	0	14	29	34	71

felt that the robot was not cooperating with them in order to accomplish the task (Q.6).

Finally, user responses firmly endorsed the perception of increased safety of Anticipation condition, as approximately 70% of the participants would feel safer to collaborate with a real robot in this condition. Rest 30% preferred Prevention condition and none the Control Condition (Table 5).

4. Discussion

Every new technological development brings benefits and new opportunities, but also new concerns and risks. The rapid growth of the robotics field and the emerging possibilities that the new forms of human-robot collaboration offer, have led to an ever-increasing use of robot partners on a daily basis. As Human Robot Collaboration in manufacturing and various other fields starts to become a viable option, the need for further study about the aspects that influence it becomes essential. However, these unprecedented forms of collaboration require new forms of communication between the human and the robot, mutual understanding and awareness of the collaborator's situation, and the establishment of a predictive mental model regarding the partner's operation.

The aim of the present study was to explore how human anticipatory behavior or robot adaptiveness affect joint Human - Robot task efficiency, fluency and safety in an industrial HRC task. Specifically, it seek to explore the effects of (i) robot's visual commissive cues on fostering human anticipatory behavior and (ii) to compare the latter method with a more widely studied alternative in the form of robot adaptiveness (i.e. prevention mechanism) to human actions. Although it is definitively possible to combine robot's visual commissive cues and a prevention mechanism in the same HRC task, in this experiment it was decided to treat these as two alternatives to compare their respective merits.

Human safety was measured quantitatively through the Number of Collisions occurred, task efficiency through Task Completion Time and collaborative fluency through Human Idle Time. Overall, the results from the data analysis supported the hypotheses made in a solid way. In the Anticipation condition the measures were greatly improved in all three metrics compared to the Control condition, while in Prevention condition safety was clearly improved, however with no significant increase in task efficiency and fluency compared to the Control condition. It should be noted though that, the results obtained regarding collisions should be treated as only indicative since in a real industrial setting people are expected to behave with more caution than they do in VR.

Specifically, in Anticipation condition evidence from the analysis of Total Collisions provided strong support regarding the hypothesis that anticipatory cues improve safety. Especially, as it is reported above, the collisions among the participants and the robot were considerably fewer. It should be noted that, the increased safety of this condition was also recognized by the participants as derived from their answers on subjective condition preference. Moreover, the analysis of Total Task Completion Time confirmed the hypothesis that the specific anticipatory cues improve task efficiency. Overall, the task was accomplished in much shorter time compared both to Prevention and Control conditions. Finally, regarding Human Idle Time, data analysis verified the hypothesis that anticipatory cues positively affect fluency of the collaboration. Specifically, when the human was able to predict the target of robot's motion he/she spent considerably less time being idle.

In Prevention condition, the analysis of Total Collisions supported the hypothesis that reducing the robot's movement speed while in close proximity with the human increases safety as the total number of collisions significantly decreased, compared to Control. On the other hand, the hypothesis that robot's speed reduction would have a negative effect on task efficiency failed to meet, as there was no significant increase in Task Completion Time compared to Control. This result however was strongly influenced by the specific experimental setup. As mentioned above, when a collision occurred the robot retreated to a safe position until the human resumed the process by pressing the appropriate button, resulting in this manner in an increase in task time. Therefore, in the specific experimental set-up, a collision costs more in time delay than a slowdown of the robot and so the time lost due to more collisions in the control condition compensated the time lost due to slowdowns in the Prevention condition. In a different experimental setup results might have been different.

With respect to the possibility that learning effects within each condition affected performance it was noticed that in the 1st set of balls of Prevention condition, even though fewer collisions occurred in absolute numbers, no statistically significant difference was found compared to Control. To the contrary, in Anticipation condition the collisions were considerably fewer both in the total and in the separate sets. Consequently, it can be deduced that in Prevention condition it took some time for participants to become acquainted with the robot adaptiveness, in contrast to Anticipation where participants did not find any difficulty in taking full advantage of it from the start.

Despite the positive impact of anticipatory cues on overall safety and performance in the particular experimental task, a possible side-effect of anticipatory cues could be that these may affect participant task strategy. During the analysis of video material two primitive task strategy types came to authors' attention: aggressive-risky and defensive-cautious. No reliable objective metric could be established however in order to statistically test the effect of strategy type on performance or the effect of condition on strategy type. An interesting research question regards whether foreseeing the robot's next move may affect participant's task strategy towards risk-proneness. Further research is needed for investigating this issue.

The present study is a part of an ongoing research aiming to investigate the benefits of fostering anticipatory behavior of the human operator in HRC. Particularly, the research explores appropriate communicative means aiding the operator in predicting the robot's arm imminent movement or intent and in planning his actions accordingly. Overall the results suggest that communicating robot intent information to the human just before robot movement becomes legible may significantly improve collaboration by taking full advantage of the inherent human flexibility and adaptiveness. It should be mentioned though that the predictions and communicative cues implemented in this study (i.e. prediction of the robot's imminent movement and ball coloring) are case-specific; their application in other collaborative tasks may prove more challenging depending on the specific case. Typical challenges include the type and physical implementation of anticipatory signals/cues as well as the available time delay between controller calculations and actual robot arm movement. Nevertheless, such predictions are possible to be obtained in many industrial systems, when imminent path planning is available before physical robot motion by an adequate time margin (e.g. 1–5 s), and where effective communicative means can be implemented. It should also be stressed that the particular experimental task was not meant to simulate any particular industrial scenario. It was deliberately designed with the purpose of creating challenging situations for the human participant, in order to investigate the effect of a specific design feature (i.e. anticipatory cues). Therefore a number of simplifications were made concerning safety requirements that would apply in any real industrial application. On the other hand, there are several industrial tasks, which include repetitive actions, or tasks with separate and distinguished roles among humans and robots collaborators, where it might be argued that anticipating imminent moves and intents is not really necessary. However, even in these cases it remains critical to help humans infer the rules and the strategies that the robotic collaborator has during its planning and decision making phase or to prevent collapse of collaboration when an unexpected breakdown occurs, so anticipatory behavior may prove beneficial for such cases also, although to a lesser degree.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The authors would like to thank all the people who participated in the aforementioned experiments for their time and collaboration, as well as all our colleagues who developed the wearable motion tracking system. This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

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