

How a Minimally Designed Robot can Help Implicitly Maintain the Communication Protocol

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Abstract With an increasing demand for minimally designed robots, the research field of human–robot interaction (HRI) has to meet new and challenging requirements. One of these challenges is in the difference between the user’s retained mental model consisting of the instructions triggering the robot’s different behaviors and the robot’s previously taught instructions by the user. More specifically, we mention here the divergence between what was remembered by the non-expert user or believed taught to the robot in a previous HRI instance and what was actually taught to it. This divergence could lead to a waste of time when the robot is reused before it could be used effectively to achieve a task. Some users may not have the patience to reteach the robot a new version of instructions or what we call a communication protocol (CP) if they realize that they have forgotten the previous version of CP. In our previous work, we studied how a non-expert user could establish a CP in a context that required mutual adaptation using a minimally designed robot named sociable dining table (SDT). SDT is a dish robot, placed on a table which behaves according to knocks issued by the human. The human knocks on the table to convey an instruction in order to make the SDT undertake a specific behavior. The SDT had to learn through the received knocking how to choose the correct behavior. We remarked, based on previous experiments, that a CP could be built incrementally during the HRI. The formed CP was not only personalized to the pair of the non-expert user and

robot, but also to the HRI instance. This means that the CP changed each time the human started a new interaction session with the SDT. The main reason behind the change was the non-expert users’ forgetfulness of the previously established communication protocol (PECP) and their issuing of a different set of new instructions to the SDT rather than maintaining the old instructions and continuing to teach the robot new skills. In the current study, we investigate how we can modify the way the minimally designed robot communicates back to the human so that the CP could be maintained and time wasted constructing a new CP could be avoided. This paper describes feedback strategies combining inarticulate utterances (IUs) with the minimally designed robot’s visible behaviors, to trigger an increased remembrance of the PECP. The results provide confirmatory evidence that using IUs combined with the minimally designed robot’s visible behaviors assist in driving non-expert users to maintain the PECP and avoid time wastage and task achievement failure.

Keywords Dual coding · Inarticulate utterance · Protocol of communication · Recall

1 Introduction

The use of robots in our daily life has long been a goal of roboticists. This goal alludes to robots being able to cooperate and communicate, but also learn from their human partners [1,2]. Several realms related to different disciplines such as machine learning [3], ecological psychology [4], etc. are actively working towards the goal of making a robot teachable. In order to efficiently learn from interactions with non-expert users, robots do not only need sophisticated machine learning algorithms, but attention should be given to how non-expert users teach robots [5]. A good teacher

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should maintain an accurate mental model of the robot's state (e.g., what is understood so far, what rules of interaction (CP) have been established that could be considered as basic blocks in order to construct more complex rules in the future, etc.) in order to improve the robot's learning behavior. The robot, in turn, helps the teacher by making its learning process transparent through an expressive feedback strategy. It should demonstrate its current knowledge and mastery of the task [6,7]. Through this reciprocal and tightly coupled interaction, the teacher and the robot cooperate to simplify the task of CP construction and maintenance. However, this tradeoff is far from being easy to achieve as numerous challenges are encountered when we have a minimally designed robot coupled with a non-expert user.

Although, according to some HRI studies [8–10], human feedback can help a robot to learn a rich representation of the task and skills using reinforcement learning (RL),¹ humans may not have the expertise to provide accurate high-level feedback.² A non-expert user is a robot user that may introduce ambiguous or very complex instructions. Some studies [11] identified a non-expert user as a human who gives incompatible instructions to make a robot learn a new skill even if they are used to using robots. One of the behaviors a non-expert user could adopt is using the reward channel not only for feedback, but also for future-directed guidance [11]. They could also possibly have a positive bias by using the reward signal as a motivational channel. They may accidentally change the instruction related to a previously taught behavior to the robot while they are supposed to maintain the same instruction [11]. These issues are difficult to resolve when we have a minimally designed robot rather than an expensive multi-modal robot.

The minimal design concept was first proposed by Matsumoto et al. [12]. Matsumoto et al. [12] concludes that the robot's appearance should show minimal use of anthropomorphic features, so that humans do not overestimate or underestimate the robot's skills [13]. By minimal design, we mean eliminating non-essential components and keeping only the most fundamental functions. Thus, we could define a minimally designed robot as an affordable robot which includes only the essential sensors that may guarantee a minimum of sociability and whose appearance is simple in terms of anthropomorphic features. We expect that, in the future, minimally designed robots will be more affordable than other multi-modal robots [14]. People will use such minimally designed robots for a variety of tasks

and services. As an example, one can mention “cleaning the floor” with Roomba the robot [15]. Interacting with such minimally-designed robots may represent the first experience of a non-expert user interacting with a robot. This leads us to assume that non-expert users will possibly have high expectations about the robot's adaptive capabilities [16]. They expect that a robot should show an obvious obedience when a non-expert user assigns an instruction to it. As a result, in the case of minimally-designed robots, the probability of an inconsistent feedback strategy afforded by the non-expert user during CP construction or reuse, can increase for multiple reasons.

First, the non-expert user may assign the same instruction each time in a different way whereas they should stick to what they taught to the robot previously. If the instruction related to a specific behavior is changed by the human, the robot may adapt to the new instruction. Teaching the robot the same behaviors each time when the robot is supposed to be reused may lead to time wastage for the user before the robot can be used effectively. In addition to that, as long as the non-expert user cannot see that they should adhere to rules (CP) previously taught to the robot (PECP), they may in turn blame the robot for being non adaptive. In such a case, a non-expert user will likely stop using the minimally designed robot.

In this vein, in order that the long-term use of minimally designed robots could be guaranteed, a primary challenge that should be resolved here is the increase of PECP remembrance. In fact, through the reciprocal and tightly coupled interaction that we presented there is a weak point of “having a good teacher” (since we address the problem of having a non-expert user). That it is why, the other node (the robot) of the reciprocal interaction should be strengthened to maintain the equilibrium. The minimally designed robot should guide the non-expert user by making its learning process more transparent to them through an expressive feedback strategy.

We expect that the new expressive feedback strategy (the combination of IUs with the robot's visible behaviors)³ which can be used by the minimally designed robot may reduce the cost of PECP modification because of the user's forgetfulness without reducing the robot's final, asymptotic performance. Even though a minimally designed robot cannot use multiple communication channels the feedback strategy should be sufficiently expressive to guarantee sociability, a decrease in PECP forgetfulness and be of low cost.

One of the main theories of Paivio in the context of CP retrieval or more generally in the domain of information recall is the dual coding theory. Paivio proposed the idea

¹ Reinforcement learning refers to a class of machine learning problems. The aim is to learn from experience, what to do in different situations, so as to optimize a quantitative reward over time.

² Here we mention about a reward signal that should be assigned in such a way so the robot could clearly distinguish between the right and wrong behaviors. A wrong behavior is associated with a negative reward signal, while a good behavior is associated with a positive reward signal.

³ By expressive feedback strategy, we mean a feedback that makes it easy for the human to identify the wrong instructions given by him to the robot. In the current work, what we mean by new expressive feedback is a combination of the robot's visible behaviors with the IUs.

that forming mental images aids on recall [17]. Dual-coding theory postulates that sound code combined with information is used to mentally code the information [18] in the human's mind. The mental codes corresponding to these representations are used to organize incoming information that can be stored and retrieved for subsequent use. Sound codes can be used when recalling information [18] (cued recall)⁴ and facilitates information retrieval. Therefore, the main idea in our work consists of combining the robot's visible behavior with sound information (an IU) to facilitate rules coding and retrieval. During the reuse, the robot has just to generate the sound information before executing the action to reduce the error rate and time wastage that can occur when a non-expert user tries to reconstruct a new CP rather than reusing the PECP. We expect that such sound information (the IU) may refresh the user's memory and lead them to remember the correct instruction.

Previously, we designed a novel scenario where a non-expert user can use only one communication channel; knocking [14]. To communicate with our minimally designed robot SDT, the non-expert user has to knock on the table to express their instruction. The instruction may lead the robot to execute different behaviors such as: going left, right, backward or forward. The robot has to learn the meaning of the knocking, and choose an action that converges with the human's intention. We showed that we can simulate the procedure that the human uses to make the robot incrementally establish a CP.

In our current study, the main point that we focus on consists of the fact that, in each SDT-robot interaction instance (trial), we remark that the non expert user-robot pair creates a new CP that is completely different from the PECP of the previous HRI instance because of the user's forgetfulness of the PECP. We want to investigate whether users can maintain the same CP if the robot combines visible behavior and sound information (an IU) with the taught instruction. During the reuse of the PECP, the SDT will generate sound information (IU) before executing the action to reduce error rates and time wastage. We expect that this may hopefully refresh the user's memory and lead them to remember the correct instruction.

The remainder of the paper is structured as follows: In Sect. 2, the related work; Sect. 3 exposes the Setup; Sect. 4 is related to study performance; Sect. 5 describes the results. Sections 6, 7 and 8 are related respectively to discussion, the implications of the study and the limitations of the research.

2 Related Work

Since the proposed study and its experimental evaluation are motivated by theories from social psychology, design concepts and studies from HRI, this section provides an overview on relevant theoretical foundations in human–human interaction and design concepts as well as HRI related work.

2.1 Proposed Solutions to Deal with or Prevent PECP Forgetfulness in HRI

In this subsection, we will expose different methods presented in the HRI that can be categorized into two types; implicit and explicit, before explaining more about the inspirational motives behind our choice of IUs and the robot's visible behavior combination.

2.1.1 Explicit Methods

In the context that it is the forgetfulness of the PECP occurring during the HRI, by explicit methods we mean deliberative messages. These messages afford direct conclusions to humans in order to argue with them, reject their request or make a confusing proposition.

Several studies successfully explored problems arising from users giving commands to an artifact executing instructions [19,20], as well as related error handling that is integrated in spoken dialog systems [21]. Error handling through the usage of spoken speech may cause lexical or conceptual difficulties and the robot may not be able to cope with the complexity and vagueness of natural language [22].

Argumentation was another proposed solution [23]. Argumentation consists of deriving reasoning semantics by analyzing supports and defeats [24]. The robot should ask the human for more information that may help it obtain the complete context during HRI. That it is why, inquiry and information-seeking dialogues could be employed to resolve interaction errors due to PECP forgetfulness [25]. However, in this case, we put at risk the HRI because a non-expert user is not supposed to deal with a robot that wastes their time with argumentation instead of executing actions.

Other HRI studies, went beyond Asimov's laws of robotics and found that it is possible to reject a human's request. For that, some directives were suggested in [26]. We believe that a robot has to avoid negatively framed speech, including rejecting human requests, because it threatens the user's social face. A social face is related to a human's concern of maintaining a good public image [27]. Any act that goes against the maintaining of a good public image is considered to be a face-threatening act [28]. People have a tendency to treat others much as others treat them. In a case where a robot rejects a human, according to the law of reciprocity, humans will sooner or later do the same [29].

⁴ It is a cued recall because the robot tries to help the human to remember the rules by presenting cues which are in a sound format.

By extending the line of our research we believe that a speech act during an HRI has to support the human's social face, but ought not to be used to increase their frustration through disagreeing with their propositions [30]. Furthermore, another more challenging point is related to the robot's minimalistic design that makes it difficult to include a defeating speech rejection, arguing or pointing out the human's errors. A minimalistic robot that does so may lead to an adaptation gap resulting from the difference between its minimalistic appearance and its role as an authority that may dictate to the human how to interact [31]. It may lead to a decrease in the robot's likeability and perceived competence. Consequently, we avoid using an explicit method. We prefer to use an implicit method that helps to support the human's social face and diffuse any frustration.

2.1.2 Implicit Methods

By implicit methods, in the context that it is PECP forgetfulness occurring during the robot's reuse, we mean non deliberative (indirect) information that helps shape indirect conclusions during the HRI in order that users change their attitude and pay attention to the instructions given to the robot. Specifically, the robot should not express to the human directly, through explicit speech, that they have to change their behavior. The robot has to use a subtle cue that may influence indirectly the human's thinking to give the right instruction. People are more persuaded by information that does not seem to be designed to influence them because they do not realize when the information is over there and they let down their guard. There have been many studies in HRI that discuss implicit methods to guide the human to pay attention to their behavior [11, 32].

Some studies used a pseudo-implicit method that provided forewarning. An instructor told the participant how to use the robot before the interaction started [11]. In [32], a whiteboard near Simon (the robot) was provided as a reminder about the concept representation and the types of sentences that the teacher could say.

Informing the human before the interaction starts just like in [11], may lead to a human's confusion about the instructions. Forewarning may also increase the feeling that the interaction is not quiet or natural and it is not useful when the amount of instructions organizing the interaction increases. Finally, writing on the board, to remind the person of the taught concepts to the robot, is also inconvenient because it is not a natural communication channel and is contrary to the HRI community goal to make the communication intuitive and natural [32].

Moon et al. [33] straddled the line under the usage of hesitation gestures in collaborative tasks while indirectly transferring to the human information that PECP forgetfulness is occurring during the HRI. This implicitly may cause

a trust problem because a non-expert user could define these hesitation gestures as a robot that may generate errors in the future [34].

2.2 Inspirational Points

As we highlighted in the introduction, we need an expressive method that will empower the interaction between a minimally designed robot and a non-expert user so that the user's forgetfulness of the PECP can be avoided. The proposed solution should respect the fact that the robot is minimally designed and be harmonious to its simple appearance so as to not lead to an adaptation gap. The suggested method should also operate on the robot's expressive feedback rather than relying on the non-expert user to focus like an expert teacher on the HRI process. According to the presented HRI studies, an implicit method could be more powerful to indirectly shape a human's retrieval of the PECP because it is not face threatening.

2.2.1 Inarticulate Utterances (IUs) as an Expressive Feedback Strategy

Adults are capable of communicating through actions, voice, language and symbols. A child can use hummed sounds. Even though there are limited means of communication between a caregiver and a child, both parties still can interact and reuse PECP that may facilitate their daily interactions [35]. This is undoubtedly of great value and significance in being a source of inspiration to resolve the issues related to our study. People accept the use of hummed sound or what we call IUs. They are able to establish a CP via IUs and remember the PECP during future child-caregiver interactions. That it is why there is also a possibility that the same thing may occur when we use the IUs during the HRI. As a result, inspired from the child-caregiver interaction, we expect that using IUs during the HRI can be considered by non-expert users as a natural way of communication. Also, we think that using IUs can easily lead to CP formation and PECP retrieval just as in a child-caregiver interaction.

We define IUs as short auditory icons consisting of hummed sounds which are used as social cues during an HRI. IUs consist of utterances designed to resemble natural language, but have no linguistic semantic content [35]. We argue that people readily attribute meaning to novel IUs as suggested by some HRI studies [36, 37]. As meaning can be attributed to these IUs, combining them with a robot's visible behaviors may lead to an increase in PECP recall in future interaction instances if the robot presents the IU before executing the corresponding action (cued recall). Dual coding in this context, consists of combining the IU with visible behavior [38]. Finally, using IUs suits the minimally designed robot

because it would not require expensive extra tools for them to be integrated.

2.3 Variation-Repeat Feedback Strategy

Whilst diversification has many implications, it is generally accepted that diversification is good [39]. Diversification of the robot's output is desirable during social interaction. It represents new events and changes generated by the robot via behavior-generating algorithms which may arouse people's curiosity to discover yet unpredictable regularities in the robot's behavior. Diversification is always involved from a person's behalf during the meaning construction of the newly evolved behaviors. It requires that the robot adapts to the humans [40] and in addition to that. Users will start to more readily believe that the robot is somehow a conscious agent [40]. Thus the perception of the robot by human users is always positive and may not decrease over time.

The first studies on the temporal progress of user experience in households equipped with a robotic vacuum cleaner indicate an initial enthusiasm in human users. However, any enthusiasm may decrease over time due to habituation to the robot's feedback [41]. Interactive robots may even raise initial enthusiasm [42], but in some cases humans may be willing to explore the limits of robots, as observed in robotic applications developed to operate in public spaces, where even a bullying type of behavior was shown by human passers-by towards the robot, e.g. [43].

When a person initially likes a simple advertisement, they do not wish to hear it repeated too many times or advertisement wear-out might occur. Wear-out is a condition of inattention and possible irritation that occurs after a person encounters a specific advertisement too many times [44]. They may remember letter by letter the advertisement's message but may dislike the message or try to avoid hearing it over and over. One good way to prevent message wear-out is to use repetition with a variation-repeat of the same information [45]. That is why, in our current study, we intend to add a technique of variation-repeat so that the robot can propose different IUs per the robot's visible behavior. Thus, the human can avoid this state of IUs wear-out which may influence their perception of the robot even if the PECP could be retrieved because of the repetition.

3 Setup

The subsections below outline the robot's architecture, behavior learning algorithm (actor/critic algorithm), IUs generation method and variation-repeat IUs generation technique.

3.1 Hypothesis

Our study sought to test the central hypothesis that, by using IUs combined with the robot's visible behaviors, the robot will be capable of displaying expressive feedback for the non-expert user eliciting a better remembrance of the PECP and a better user perception of the robot's overall performance. We consider the time needed to recall the rules of the PECP, the number of recalled rules related to the PECP and the task completion time as measures that might elucidate whether there is a better remembrance of the PECP. A better user's perception of the robot's overall performance corresponds to a better perceived competence of the robot by the human, better human social face support and better robot likeability. We summarize our hypothesis as follows:

Hypothesis 1 Using the robot's visible behaviors as the only feedback strategy during meaning construction and retrieval will decrease the human's social face support as well as his perception of the robot's competence and likeability.

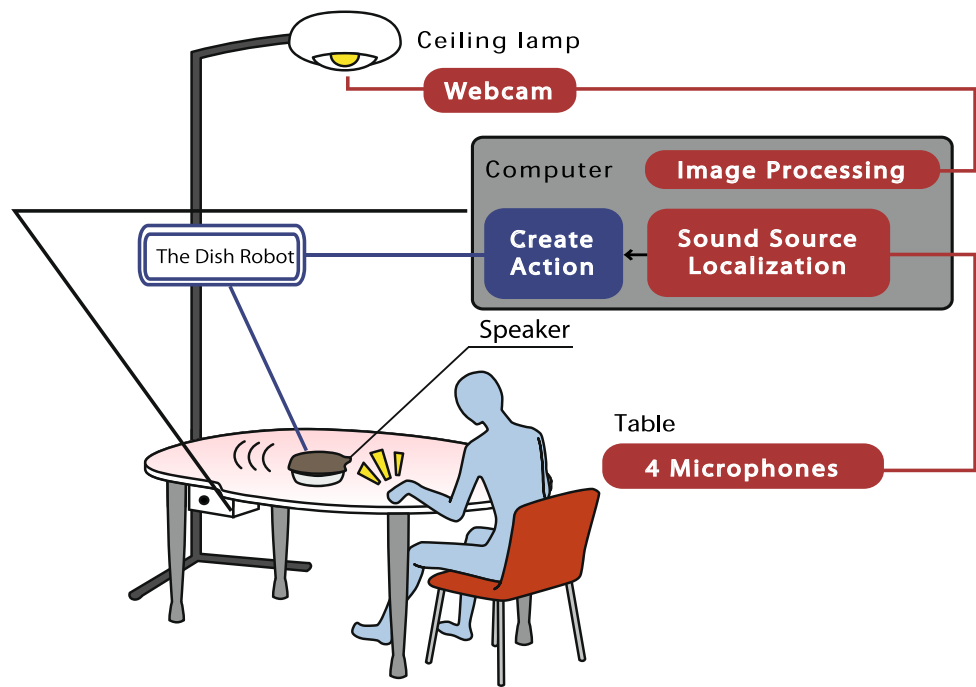
In this context, we compare the user's perception of the robot's overall performance and his remembrance of the PECP when the robot uses its visible movement as the only feedback during meaning construction and retrieval. This comparison may help to highlight the challenges that the HRI encounters when the robot uses its visible movement as the only feedback.

Hypothesis 2 Combining IUs with the robot's visible behaviors during CP construction and retrieval improves the user's remembrance of the PECP where the time needed to recall the rules of the PECP and the task completion time will decrease while the number of recalled rules corresponding to the PECP will increase. Combining IUs with the robot's visible behaviors during CP construction and retrieval will also increase the human's social face support as well as his perception of the robot's competence and likeability.

Furthermore, we believe that using the same ensemble of IUs during the encoding (during when the CP construction) and the recall (during CP retrieval) phases is essential to retain the CP while changing the IUs during the recall might cause confusion. That is why, we formulate hypothesis 3 as follows:

Hypothesis 3 Changing IUs during the recall phase might decrease the user's remembrance of the PECP where the time needed to recall the rules of the PECP and the task completion time will increase while the number of recalled rules corresponding to the PECP will decrease. Moreover, changing IUs during the recall phase will decrease the human's social face support as well as his perception of the robot's competence and likeability.

Fig. 1 The overall architecture of the SDT: the human's knocking is detected by four microphones. The robot executes different behaviors using the servomotor. The speaker is used to generate different audio outputs which are the IUs



If this hypothesis could be validated, we could confirm that IUs played a key role in boosting PECP recall. Finally, we believe that repetition of the same IU when the robot is supposed to execute a specific behavior might lead to the user's boredom and that diversification could ensure better user's perception of the robot's overall performance. In the current study, diversification consists in using a variation-repeat technique. Our variation-repeat technique consists in combining three IUs for each of the robot's behaviors. For example the robot assigns $E1^5 = (A, B, C)$ to forward, (D, E, F) to right, (G, H, I) to left, etc. Thus we could draw the following hypothesis.

Hypothesis 4 Affecting more than one IU to the same robot's behavior while each IU could not be assigned to more than one robot's behavior improves the user's remembrance of the PECP where the time needed to recall the rules of the PECP and the task completion time will decrease while the number of recalled rules corresponding to the PECP will increase. Moreover, changing IUs during the recall phase will decrease the human's social face support as well as his perception of the robot's competence and likeability.

⁵ E1 refers to the first ensemble (E) of IUs that could be generated to indicate that the robot is about to execute the forward behavior. The IUs used in the ensemble E1 do not figure in the E2 to avoid any kind of confusion. For example, the user may listen (if we suppose that A, B and C are IUs) to one of the three IUs A, B or C when the robot is about to execute the forward behavior, etc.

3.2 SDT Architecture

Our system utilizes a webcam to compute the robot's position and its angle of orientation. The robot's coordinates are only used for further analysis purposes (Fig. 1). They are not used by the robot to guess the correct behavior. Knocking is the only input that the robot responds to in order to establish the correct behavior (going right, left, backward or forward). The robot uses four microphones to detect the knock based on a weighted regression algorithm [46]. It communicates with the host computer via Wi-fi using a control unit [a macro computer chip (AVR ATMEGA128)] and employs a servomotor to exhibit the different behaviors. A small speaker emits the generated audio output. Finally, five photo reflectors are utilized to automatically detect the boundaries of the table and avoid falls.

3.3 Actor–Critic Algorithm

We conceived an actor/critic algorithm that provides the robot with the capability to adapt to human preferences [14]. The human has to knock on the table in order to express their intention of making the robot move in a specific direction [four behaviors (right, left, back, forward)]. The actor/critic algorithm helps the robot to choose between the four behaviors on the basis of the received knocking and previously acquired knowledge. Finally, each human–robot pair can establish a personalized communication protocol.

Actor/critic algorithm is a reinforcement learning algorithm that, based on a reward, reinforces the execution of an

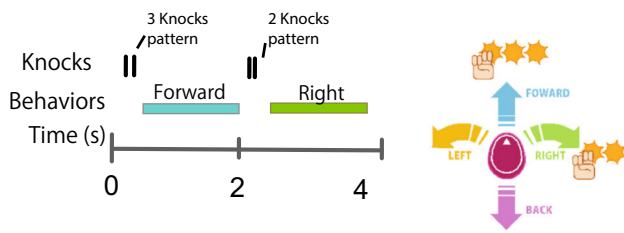


Fig. 2 A scenario showing an example of a short interaction between a user and SDT

action when a certain input is afforded to the system or inhibited by calculating a temporal difference (TD) error [47]. A TD error is the difference in value between what is expected as a new state and what is actually perceived by the system as a real new state. The TD error includes a small factor related to the probability of error occurrence when the system tries to perceive the new real state and the sensors failed to detect.

While learning, the robot has to choose an action. The part of the actor–critic algorithm that is responsible for the action's choice is the actor part. The critic criticizes the action chosen by the actor while estimating the value function. A value function provides an idea about the value of being in state “S”. The critic must learn about, and critique, whatever policy is currently being followed by the actor.

3.3.1 Knocking Pattern Design Space

In our previous work [14], we remarked that there are two types of patterns: continuous-knocking patterns and command-like patterns. Command-like patterns consist of combining each behavior with a different combination of knocks (e.g., 3 knocks for forward). Continuous-knocking was used when there were contiguous interruptions in the robot's behavior.⁶ We counted the number of both types of patterns based on the coded data of our previous work for each participant and for the two trials. We noticed that there was significant usage of command-like patterns.

Users in our previous work were debriefed. Participants confirmed through most of their answers that they wanted to simplify the input for the robot in a way that they attribute modulated knocking. As an example, one can attribute 3 knocks when they want the robot to move forward and 2 knocks when they want for example to make the robot move to the right (Fig. 2), etc.

3.3.2 Actor Learning

Each knocking pattern (e.g: 2 knocks pattern) has its own distribution $X(s_{act}) = N(\mu_{X(s_{act})}, \sigma_{X(s_{act})})$ where $X(s_{act})$

is defined as the knocking pattern, $\mu_{X(s_{act})}$ and $\sigma_{X(s_{act})}$ are the mean value and the variance. Actually in our previous work [14], we conducted a human–human interaction to verify how people design the knocking space. We explained that we assign a normal distribution for each knocking pattern. The mean corresponds to the action that is the most recently attributed to the knocking pattern. The variance expresses that there is a collection of actions that could be assigned to the knocking pattern.

We chose 2 s as a threshold for the user's reaction time based on previous established experiments [14]. When the robot observes the state s_{act} (a new knocking), a behavior is selected according to the probabilistic policy $\Pi(s_{act})_{nbknocks}$. If within 2 s there is no knocking pattern, the robot has succeeded otherwise it has failed (if a knocking is received before that 2 s elapses) by choosing the correct behavior and the critic updates the value of the executed behavior in the state s_{act} . The system switches to the state s_{act+1} . If a new knocking pattern is composed before 2 s has elapsed, that means that the knocker disagrees with the behavior that was just executed. The critic updates the value function before choosing any new behavior in order that the chosen action can be maintained in the normal distribution or discarded. As long as the knocker is interrupting the robot's behavior before 2 s has elapsed, the actor chooses henceforth the action by pure exploration (until we meet an agreement state about the chosen s_{ac} : no knocking during 2 s) based on (1). The random values vary between $0 \leq rnd1$, and $3 \leq rnd2$. The above range was decided in order to bring the values of the action between 0 and 3 (corresponding to the behaviors (forward, right, backward, left) numerical codes). We assume in such cases that the knocker will randomly compose patterns just to switch the robot's behavior.

$$A_{ac}(s_{act}) = \mu_{X(s_{act})} + \sigma_{X(s_{act})} \times \sqrt{-2 * \log(rnd1)} \times \sin(2\pi * rnd2) \quad (1)$$

3.3.3 Critic Learning

The critic calculates the TD error δ_t as the reinforcement signal for the critic (2)

$$\delta_t = r_t + \gamma V(s_{act+1}) - V(s_{act}) \quad (2)$$

with γ as the discount rate and $0 \leq \gamma \leq 1$. According to the TD error, the critic updates the state value function $V(s_t)$ based on (3).

$$V(s_{act}) = V(s_{act}) + \alpha \times \delta_t \quad (3)$$

where $0 \leq \alpha \leq 1$ is the learning rate. As long as the knocker disagrees about the executed behavior before 2 s elapsed, we

⁶ Continuous-knocking was related to the presence of contiguous disagreements about the shared rules.

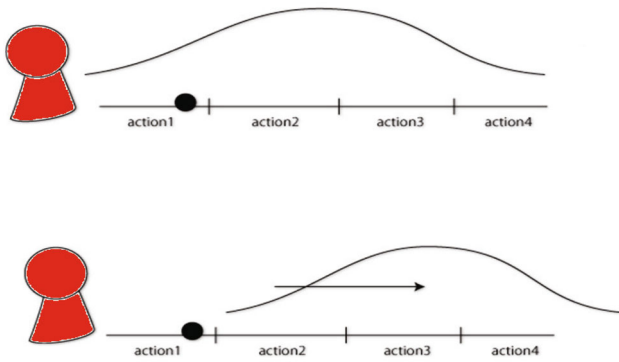


Fig. 3 A normal distribution corresponding to a knocking pattern (instruction) can shrink if an action is to be discarded

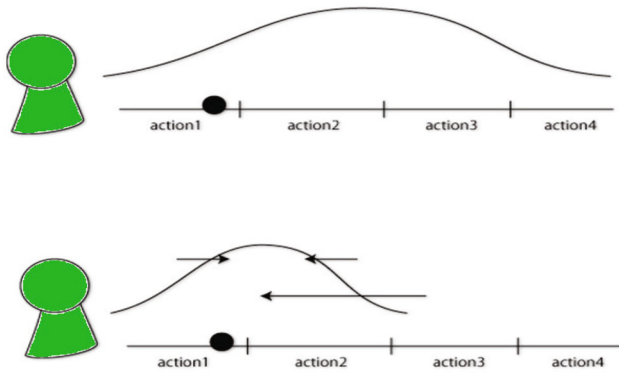


Fig. 4 A normal distribution corresponding to a knocking pattern (instruction) can approach more the numeral code of the new action if the new action was a correct one

refine the distribution $N(\mu_{X(s_{act})}, \sigma_{X(s_{act})})$ which helps us to choose the action according to (4) and (5).

$$\mu_{X(s_{act})} = \frac{\mu_{X(s_{act})} + A_{ac s_{act}}}{2} \quad (4)$$

$$\sigma_{X(s_{act})} = \frac{\sigma_{X(s_{act})} + |A_{ac s_{act}} - \mu_{X(s_{act})}|}{2} \quad (5)$$

During the update, a normal distribution corresponding to a knocking pattern (instruction) can shrink if an action is to be discarded (Fig. 3) or moves in a way that the mean of the normal distribution approaches more the numeral code of the new action if the new action was a correct one (Fig. 4).

3.4 Dually Coded Feedback Strategy

An IU consists of a single tone and prosodic component without any articulation or phonemic. We used the architecture proposed by Okada et al. [48] so that we can generate IUs. We used this system so that we can ensure that the IUs that are generated are suitable for the robot's appearance [49]. The system works as follows (Fig. 5): We asked a volunteer to read the utterances aloud. The volunteer's voice is cap-

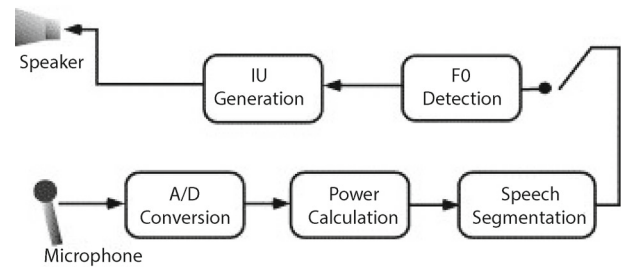


Fig. 5 Outline of the front-end modules used for capturing the speech and processing the signal to generate a sequence of frames comprising of the voice-only portions in the utterance: the goal of this processing is to translate the sound uttered by the user—which is received in the device as a series of amplitude samples from its microphone and analog-to-digital (A/D) converter—into a representation suited for the generation of a feature descriptor that corresponds to an inarticulate utterance

tured and sampled at 16 kHz (A/D conversion; e.g: some of the utterances: go forward, go left, etc.). We call the result of the sampled recorded voice x_i . After that, the time sequence of the power pattern $P(i)$ is calculated, e.g., the level of volume of the human voice, is calculated for each utterance (power calculation) P_i . The segmentation of each utterance is determined by the threshold energy based on the result of the power calculation (utterance segmentation). Then, the time sequence of an $F_0(i)$ pattern is computed (F_0 pattern detection). The F_0 patterns are experimentally detected by the average magnitude differential function algorithm [50]. The final IUs are synthesized by combining sine waves based on the power calculation and F_0 pattern (IU generation). The following equation shows an example of synthesized wave x'_i .

$$phase(i) = 2 \times \pi \times F_0(i - 1) / FS \quad (6)$$

$$amp(i) = P(i - 1) \quad (7)$$

$$x'_i = amp(i) \times (\sin(phase(i)) + \sin(2 \times phase(i)) + \sin(3 \times phase(i))). \quad (8)$$

where $phase(i)$ is the value of the phase, $amp(i)$ means the value of the amplitude and FS means the value of the sampling frequency. Each produced IU corresponds to an audio saved file that can later be called on by the SDT.

3.5 Variation-Repeat Dually Coded Feedback

Our variation-repeat technique consists of assigning each of the robot's behaviors during the encoding phase, three different IUs. For example, the robot could consider to assign (A, B, C) IUs to forward, (D, E, F) IUs to right, (G, H, I) IUs to left, etc. during the encoding phase. When receiving a knocking pattern, the robot has to decide the behavior that

should be executed and that it has chosen using the actor critic architecture. However, before the behavior is executed, it has to choose one of the three IUs that were assigned to that behavior and generates it to inform the user about the next behavior. In case the user is not satisfied, they compose another knocking pattern. For example, when deciding to execute the left behavior, the robot could choose to generate G, H or I to tell the human about the action that will be executed based on the knocking gathered by the robot. This may help to decrease time wastage and the user's negligence of the robot because they feel that it is useful since it tries to guide them to the right instruction choice and in turn may ameliorate the human's perception of the robot's overall performance, etc.

4 Study Performance

We used the workspace from our previous work to conduct a between-participants study and validate the different hypothesis that we drew.

4.1 Conditions

We included four different feedback strategies the robot may use to display feedback for the human:

- Baseline strategy (B): The robot's visible behavior is the only feedback afforded for the human.
- Dually coded feedback strategy (DCF): The robot combines each of the robot's behaviors to an IU. Each IU will be combined with only one robot behavior. If we consider that we combine (IU1, right), (IU2, forward), (IU3, left), (IU4, back) during the encoding phase (trial 1), the same combinations are maintained during the recall phase (trial 2) to facilitate PECP recall. The robot just generates the IU related to the behavior intended to be undertaken before it is executed. This may help to ameliorate the remembrance of the PECP and the user's perception of the robot's performance.
- Altered Dually coded feedback strategy (ADCF): The ADCF strategy consists in using an ensemble of IUs during the encoding phase (trial 1: CP learning) and changing it during the recall phase (trial 2: PECP recall). For example, if we consider that the robot combines (IU1, right), (IU2, forward), (IU3, left), (IU4, back) during the encoding phase (trial 1), these combinations are modified during the recall phase (trial 2) while new IUs are used rather than the ones used during the encoding phase [(IU1', right), (IU2', forward), (IU3', left), (IU4', back)]. During the recall phase, the robot generates the IU related to the robot's behavior intended to be undertaken before it is executed. However, if we suppose that the action that

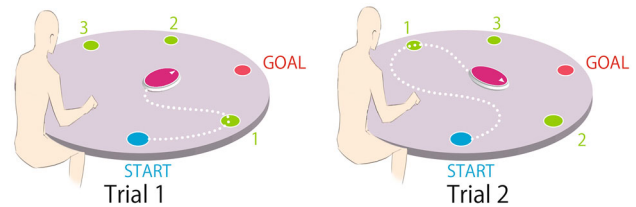


Fig. 6 In the first trial (*left*), the participant has to understand how the communication protocol is acquired in order to make the robot move into the designated locations on the table (start, 1, 2, 3, and goal) by means of knocking patterns. In the second trial (*right*), we change the sequence of the former points on the table, and then the user have to reuse the emerged rules of communication of the first trial to guide the robot into the newly defined locations

should be executed is the left direction the robot does not use IU3' to make the human remember, a new IU that the human has not used before will be generated. This may help to prove that changing the IUs during the recall may lead to a problem related to the PECP retrieval.

- Variation-repeat dually coded feedback (VRDCF) strategy: VRDF consists in assigning for each of the robot's behaviors different set (S) of IUs; for example by assigning $S1 = IU1, IU2, IU3$ to forward, $S2 = IU'1, IU'2, IU'3$ to back, $S3 = IU''1, IU''2, IU''3$ to right, etc. These ensembles are assigned in a way that any IU that it is in one ensemble could not inserted in another ensemble to avoid user confusion. The variation consists of not hearing the same IU each time the robot decides to execute a behavior. When a knocking pattern k_i is composed by the human at time t_i , a behavior b_i will be chosen according to the actor/critic algorithm. Before that the behavior b_i gets executed, there will a choice made by the robot to pick an IU from the three IUs of the set S_i related to the behavior b_i . We assume that we could avoid the user's boredom with such a strategy because the user does not have to listen to the same IU each time they have to make the robot undertake a specific behavior.

4.2 Task

In this study, before taking part in the experiment, the different guidelines are explained by an instructor (Fig. 6). The participant has to knock on the table in order to help the robot visit different points marked on the table (Fig. 7). Before the participant enters the experimental room, the instructor advised him that the purpose of the experiment is to help the robot arrive at different checkpoints marked on the table. The robot only needs to listen to the knocking, learn the meaning and then choose a convenient direction based on the knowledge gathered.

Before starting the interaction, one condition related to the robot's feedback modality is chosen randomly [e.g.: (DCF)].



Fig. 7 A participant interacting with the SDT

Conditions are chosen randomly but in a way that each condition would have been used by 20 participants at the end of the experiment. The conditions are B, DCF, ADCF, VRDF as we explained in Sect. 4.1. The interaction is video recorded. In the first trial, the participant had to cooperate in order to lead the robot to different sub-goals (Fig. 6). The participant has to finish trial 1 and then answers three questionnaires related to the robot's likeability, competence and social face support (Sect. 4.4). After one week, the participant has to visit the laboratory again and cooperate with the robot so that it can visit the new sequence of different checkpoints marked on the table (trial 2). In the second trial, we changed the coordinate sequence of the former points and the participant had to cooperate with the robot to reach the new coordinates sequence of the check points. Changing the coordinate sequence of the check points would likely guarantee that the participants were not accustomed to the configuration. Also, it helped us to confirm that the participant used their adaptation abilities during the encoding phase (trial 1) and PECP retrieval to succeed during the recall phase more specifically in the onset of trial 2. The interaction is once again video-recorded. Once the participant finishes, they answer three questionnaires related to the robot's likeability, competence and social face support (Sect. 4.4). At the end of the study, the instructor debriefs the participant. The entire procedure took approximately 35 min. The participant is thanked and received a payment of 1000 yen for their participation.

4.3 Participants

We recruited 80 participants (47 males, 33 females) placing 20 individuals in each of the unique four different setups. Participants were from diverse majors and occupations. Ages ranged from 18 to 46 ($M=22.7$, $SD=5.92$) years. All of the participants were recruited from the Toyohashi University of Technology of Japan. They were recruited through email.

4.4 Measures and Analysis

Our dependent variables reflected both objective and subjective measures.

4.4.1 Objective Measures

For each task, three objective measures described the effectiveness of the robot's feedback in helping the human to remember the PECP and achieve the task goal. These objective measures are the number of recalled rules, the time needed for the recall and task completion time. All these variables can be determined by analyzing the recorded videos.

4.4.2 Subjective Measures

The participant answers different questionnaires on seven-point rating scales:⁷ competence [51] (Cronbach's $\alpha=.73$) to evaluate the robot's competence, the social face support [52] (Cronbach's $\alpha=.81$) to verify whether the user's social face was supported during the HRI, and the robot's likeability [53] (Cronbach's $\alpha=.80$). Additionally, participants were debriefed.

4.4.3 Video Coding

After the experiment finished, the interaction scenarios were analyzed in order for us to identify the different established CPs. We analyzed the video data by annotating with a video annotation tool called ELAN. Two coders, one of the authors and one volunteer, analyzed the behavioral data captured in the video camera. We calculated the average of Cohen's kappa to investigate reliability. As a result, we confirmed that there was a reliability with $\kappa=.73$.

Videos of trial 1 help to determine the CPs (that correspond to PECPs for trial 2). The CP is composed of the interaction rules helping to control the robot. To determine the final CP rules by the end of the interaction of trial 1, the coder has to track for each direction what was the corresponding instruction (knocking pattern); e.g.: By the end of trial 1, the coder determined that two knocks were associated with the left behavior, three knocks with forward, one knock with the right behavior, four knocks were associated with the back behavior whilst continuous knocking could express the user's request for the robot to stop. By the beginning of the interaction in trial 2, the coder has to determine what was the knocking that was correctly associated with the right behavior so that the PECP (the CP of trial 1) is preserved. Changed rules indicated that the user failed to recall the rules of the PECP.

⁷ <https://goo.gl/forms/Vr6LVRDS99wBFMHX2>.

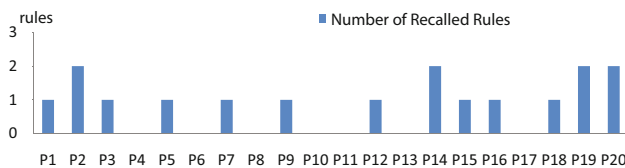


Fig. 8 The figure shows the number of recalled rules during trial 2 of condition (B)

4.4.4 Analysis

Data analysis involved paired t tests for the first hypothesis and independent t tests for the other hypothesis. G*power software was used to calculate the effect sizes.

5 Results

We discuss our results below. In each case, we cite the hypothesis that need to be tested as a reminder and then we present the results.

5.1 PECP Forgetfulness

Hypothesis 1 Predicted that using the robot's visible behaviors as the only feedback strategy during meaning construction and retrieval will decrease the human's social face support as well as his perception of the robot's competence and likeability. In this context, we compare both trials 1 and 2 of condition (B).

5.1.1 Objective Results

Figure 8 shows the number of recalled rules for participants that undertake the (B) condition. Based on Fig. 8, 35% of the participants forget completely the PECP established during trial 1, only 20% of the participants remember 50% of the PECP and no participant succeeded in remembering the entire PECP. As for task completion time, we remarked that there is a main statistical difference between the task completion time in trials 1 and 2 with t test: $t(19)=2.872$, p value = .009 < .01, $d = .642$ (paired t test between trial 1 and 2). Figure 9 shows the different subjective results as well as the task completion time of trials 1 and 2 related to condition (B). Based on Fig. 9, we notice that task completion time decreased. This can be explained by the fact that some participants remembered some rules of the PECP. The interaction time is reduced because some participants remembered some rules of the PECP.

5.1.2 Subjective Results

Based on the analysis, we remarked that there was statistically no significant differences between trials 1 and 2 in

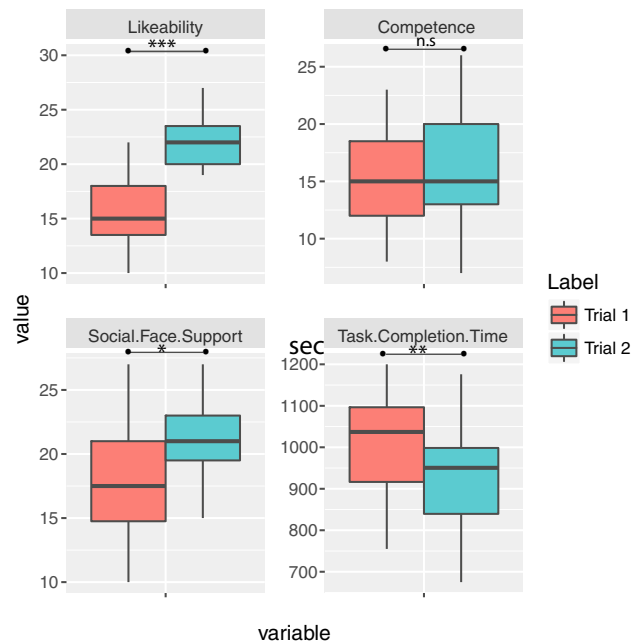


Fig. 9 The figure shows the subjective results as well as the task completion time corresponding to both trials of setup 1 (* p value <0.05; ** p value <0.01; *** p value <0.001)

terms of competence. However, there were significant statistical differences between trials 1 and 2 in terms of likeability [$t(19)=6.18$, p value <.001, $d=1.38$] and social face support [$t(19)=2.66$, p value = .015 < .05, $d = .60$; for both measures, we applied paired t tests between trials 1 and 2]. These results indicate that, although not all participants remember the rules previously established in trial 1, they still assign higher values (Fig. 9) in trial 2 for both measures: likeability and social face support.

We might explain this by the fact that participants found it reassuring to discover that the robot still remembers some of the rules of the PECP. However, they still think that the minimally designed robot is not competent enough because it does not correctly choose the right behaviors. Based on the participants debrief, participants were supporting this insight. One of the participants declared “Do I seriously have to teach the robot each time what it has forgotten?”. Another participant during the debrief said “I suppose that the robot has to be partly reprogrammed each time I need to use it. It acts like a baby; initially it will make some errors but I can see that it has learned something since the last time which is appealing but not enough.”

5.2 DCF to Maintain the PECP

Hypothesis 2 Predicted that combining IUs with the robot's visible behaviors during CP construction and retrieval improves the user's remembrance of the PECP where the time needed to recall the rules of the PECP and the task

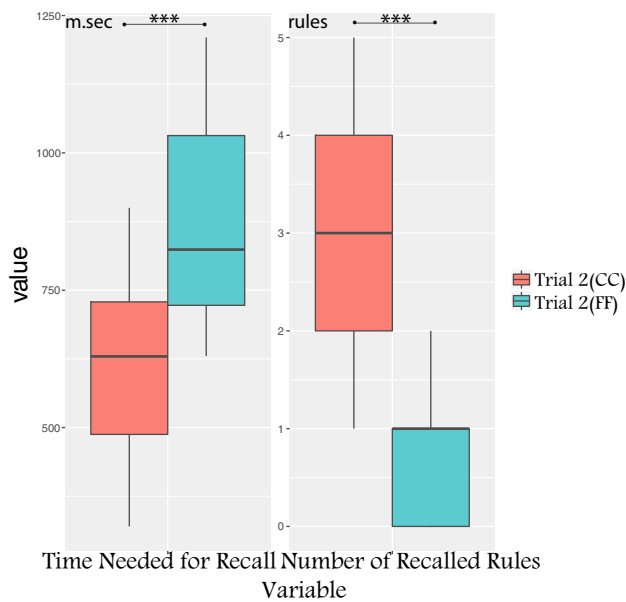


Fig. 10 The figure shows the first part of trials 2 objective results (number of recalled rules and the time needed for recall) corresponding to both conditions (B) and (DCF; * p value <0.05, ** p value <0.01, *** p value <0.001)

completion time will decrease while the number of recalled rules corresponding to the PECP will increase. Combining IUs with the robot's visible behaviors during CP construction and retrieval will also increase the human's social face support as well as his perception of the robot's competence and likeability. We compare trials 2 of conditions (DCF) and (B).

5.2.1 Objective Results

By comparing the objective measures of trials 2 related to conditions (B) and (DCF), we remarked that there are statistically significant differences between trials 2 in terms of the number of recalled rules [$t(38)=7.55$, p value <.001, $d=1.44$], time needed for the recall [$t(38)=4.57$, p value <.001, $d=2.31$; $U=23$, p value <.001] and the task completion time ($t(38)=5.58$, p value <.001, $d=1.76$). Figure 10 shows the first part of the objective results corresponding to trials 2 (number of recalled rules and the time needed for recall) of both conditions (B) and (DCF). Figure 11 shows the subjective results and the second part of objective results (task completion time) of trials 2 corresponding to conditions (B) and (DCF). Based on Figs. 10 and 11, we notice that trial 2 of condition (DCF) gives higher results in terms of the number of recalled rules and lower results in terms of the time needed for the recall and task completion time in comparison to trial 2 of (B). These results converge with our hypothesis 2. (DCF) helps to increase the recall of the PECP in shorter time which leads to

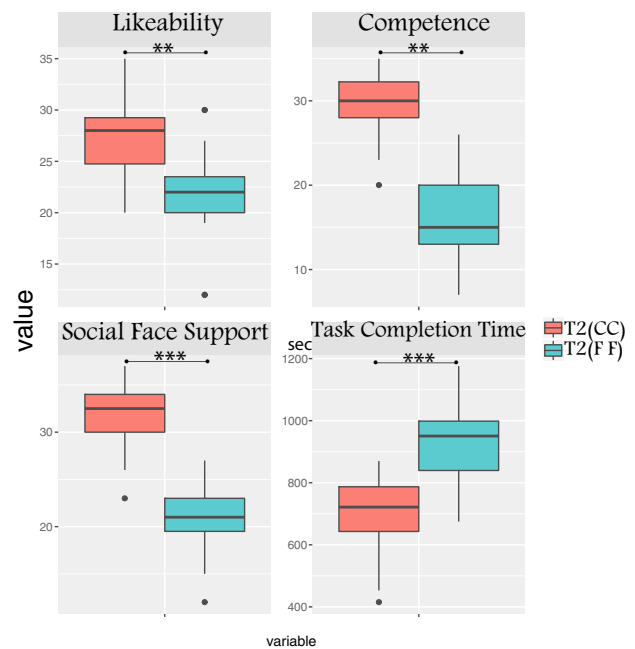


Fig. 11 The figure shows the subjective results as well as the second part of trials 2 objective results (task completion time) corresponding to both conditions (B) and (DCF; * p value <0.05; ** p value <0.01; *** p value <0.001)

shorter task completion time in comparison to a condition when the minimally designed robot uses its visible behaviors as the only feedback afforded to a non-expert user [condition (B)].

5.2.2 Subjective Results

By comparing the trial 2 subjective measures of both conditions (DCF) and (B), we remarked that there are statistically significant differences between trial 2 of conditions (DCF) and (B) in terms of competence ($t(38)=9.84$, p value=.006 <.01, $d=3.11$), likeability ($t(38)=3.95$, p value=.003 <.01, $d=1.25$) and social face support ($t(38)=9.39$, p value <.001, $d=2.97$). Based on Figs. 10 and 11, we notice that trial 2 of (DCF) produces higher results in terms of competence, likeability and social face support in comparison to trial 2 (B). These results support our hypothesis 2. The usage of IUs combined with the minimally designed robot's visible behaviors (DCF) reported significantly higher ratings for non-expert users' perception of the robot's performance.

5.3 Importance of Maintaining the Same IUs During the Encoding and the Recall of the PECP

Hypothesis 3 Predicted that changing IUs during the recall phase might decrease the user's remembrance of the PECP where the time needed to recall the rules of the PECP and

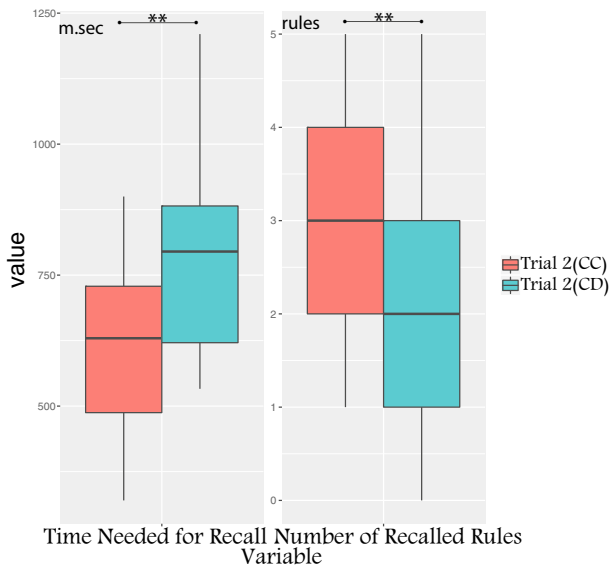


Fig. 12 The figure shows the first part of trials 2 objective results (number of recalled rules and the time needed for recall) corresponding to conditions (DCF) and (ADCF) (* p value <0.05 ; ** p value <0.01 ; *** p value <0.001)

the task completion time will increase while the number of recalled rules corresponding to the PECP will decrease. Moreover, changing IUs during the recall phase will decrease the human's social face support as well as his perception of the robot's competence and likeability. We compare trials 2 of conditions (DCF) and (ADCF).

5.3.1 Objective Results

By comparing the trial 2 objective measures of both conditions (DCF) and (ADCF), we remarked that there are statistically significant differences between trial 2 results of conditions (DCF) and (ADCF) in terms of number of recalled rules [$t(38)=2.94$, p value $=.005 < .01$, $d=.93$], time needed for the recall [$t(38)=2.91$, p value $=.005 < .01$, $d=.92$] and the task completion time [$t(38)=4.26$, p value $<.001$, $d=.88$].

Figure 12 shows the first part of trial 2 objective results corresponding to both conditions (DCF) and (ADCF; number of recalled rules and the time needed for recall). Figure 13 shows the subjective results and the second part of trial 2 objective results (task completion time) corresponding to conditions (DCF) and (ADCF). Based on Figs. 12 and 13, we notice that trial 2 of the condition (ADCF) gives lower results in terms of number of recalled rules and higher results in terms of time needed for recall and task completion time in comparison to trial 2 of the condition (DCF).

These results converge with our hypothesis 3. Changing the IUs ensemble used during the encoding phase (trial 1)

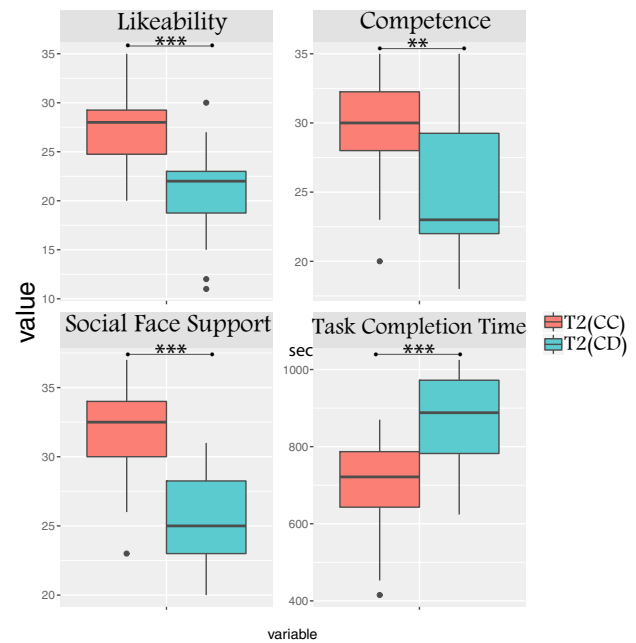


Fig. 13 The figure shows the subjective results and the second part of trials 2 objective results (task completion time) for both conditions (DCF) and (ADCF; * p value <0.05 ; ** p value <0.01 ; *** p value <0.001)

in trial 2 (recall phase) leads to a decrease in the number of recalled rules. It also leads to a longer time needed for the PECP recall and longer period of time needed to achieve the task in comparison to the condition when the minimally designed robot uses the same IUs during both phases the encoding and the recall phases [condition (DCF)].

5.3.2 Subjective Results

By comparing the trial 2 subjective measures of both conditions (DCF) and (ADCF), we remarked that there are statistically significant differences between trial 2 of conditions (DCF) and (ADCF) in terms of competence [$t(38)=3.49$, p value $=.001$, $d=.80$], likeability [$t(38)=4.83$, p value $<.001$, $d=1.55$] and social face support [$t(38)=5.34$, p value $<.001$, $d=1.05$]. Based on Figs. 12 and 13, we notice that trial 2 of the condition (ADCF) gives lower results in terms of competence, likeability and social face support in comparison to trial 2 of setup 2.

These results support our hypothesis 3. Participants answers during the debrief afforded some explanations for these decreases. One of the participants indicated: "I suppose that the robot tries to make tricks because it changed the words that were used previously. I tried to remember these sounds and whether I had heard them before. Unfortunately, I think that I forgot or that the robot tries to frustrate me!".

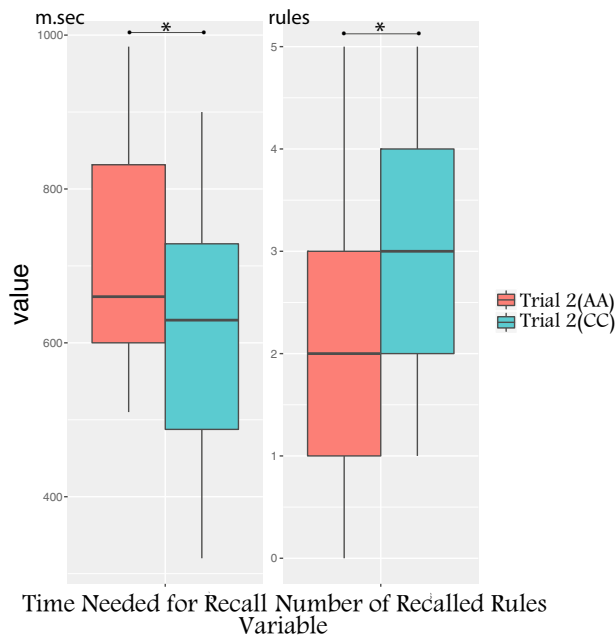


Fig. 14 The figure shows the first part of trials 2 objective results (number of recalled rules and the time needed for recall) of both conditions (DCF) and (VRDCF; * p value <0.05; ** p value <0.01; *** p value <0.001)

5.4 Evaluation of the Proposed Variation-Repeat Dually Coded Feedback

Hypothesis 4 Predicted that assigning more than one IU to the same robot's behavior while each IU could not be assigned to more than one robot's behavior improves the user's remembrance of the PECP where the time needed to recall the rules of the PECP and the task completion time will decrease while the number of recalled rules corresponding to the PECP will increase. Moreover, changing IUs during the recall phase will decrease the human's social face support as well as his perception of the robot's competence and likeability. We compared trial 2 of the conditions (DCF) and (VRDCF).

5.4.1 Objective Results

By comparing the objective measures, we remarked that there are statistically significant differences between trial 2 of both conditions (DCF) and (VRDCF) in terms of recalled rules number [$t(38)=2.56$, p value=.014 <.05, $d=.81$], time needed for the recall [$t(38)=2.02$, p value=.049 <.05, $d=.64$] and the task completion time [$t(38)=2.02$, p value=.028 <.05, $d=.72$].

Figure 14 shows the first part of the objective results corresponding to trial 2 of both conditions (DCF) and (VRDCF; number of recalled rules and the time needed for recall). Figure 15 shows the subjective results as well as the second

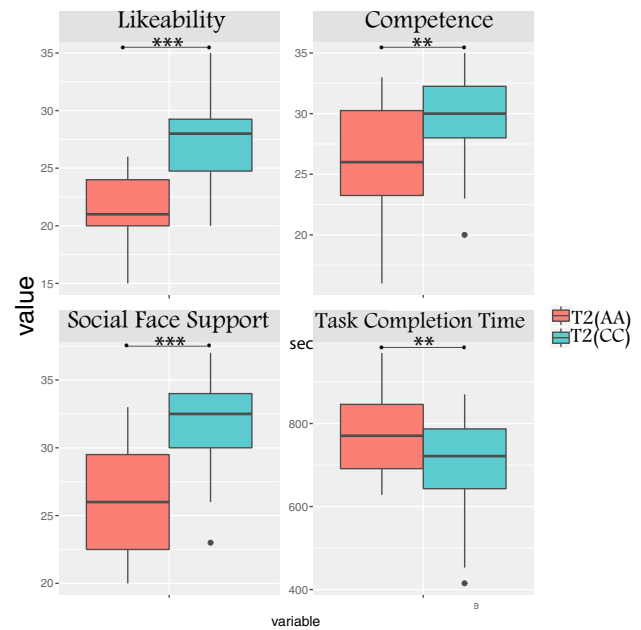


Fig. 15 The figure shows the subjective results as well as the second part of objective results of trials 2 (task completion time) for conditions (DCF) and (VRDCF; * p value <0.05; ** p value <0.01; *** p value <0.001)

part of trial 2 objective results of both conditions (DCF) and (VRDCF; task completion time). Based on Figs. 14 and 15, we particularly notice that trial 2 of the condition (VRDCF) gives lower results in terms of the number of recalled rules and higher results in terms of the time needed for the recall and task completion time in comparison to the values of trial 2 with the same measure values of condition (DCF).

These results do not meet our expectations outlined in hypothesis 4. Using a variation-repeat dually coded feedback technique (VRDCF) in a way where different IUs could mean the same instruction (knocking pattern) backfired and led to degraded performance.

5.4.2 Subjective Results

By comparing the trial 2 subjective measures of both conditions (DCF) and (VRDCF), we remarked that there are statistically significant differences between the trial 2 results of both setups 2 and 4 in terms of competence [$t(38)=2.59$, p value=.013 <.05, $d=.81$], likeability [$t(38)=5.32$, p value <.001, $d=1.68$] and social face support [$t(38)=4.56$, p value <.001, $d=1.44$]. Based on Figs. 14 and 15, we notice that contrary to what we hypothesized, trial 2 of the condition (VRDCF) produces lower results in terms of competence, likeability and social face support in comparison to trial 2 of the condition (DCF). These results do not support hypothesis 4.

Although, we enabled the robot with the capability of generating different IUs for the same behavior through the

variation-repeat dually coded feedback technique in order to avoid message wear-out and to guarantee that the non-expert user enjoys the interaction, the results indicate that in terms of objective results, performance is degraded where we have more PECP forgetfulness with such a technique. In addition, non-expert users found that the robot is less competent, less likeable and less supportive for their social faces in comparison to the same constructs values in trial 2 of the condition (DCF). Participants of the condition (VRDCF) indicated during the debrief that the robot was a bit entertaining the first time. However, during the second time (trial 2) of the condition (VRDCF) some of the participants revealed some insights which are related to the gathered results. One participant indicated: “I understand when the robot said something that it means having a chance to checkout the action before it is executed, however I get lost because I could not retain all of the spoken sounds that correspond to the same action. There were a lot of sounds right!” This means that increasing the number of IUs per robot’s behavior can backfire even if the human may like it the first time.

6 Discussion

6.1 Hypothesis 1: Illustration of PECP Recall Problem

Hypothesis 1 predicted that using the robot’s visible behaviors as the only feedback strategy during meaning construction and retrieval will decrease the human’s social face support as well as his perception of the robot’s competence and likeability. The results provide conditional support for this hypothesis and, more importantly, suggest that although on an objective scale the PECP recall was degraded, users still think that the robot is likeable and supportive for their social faces (Fig. 9). In fact, by recalling some of the PECP rules, some participants felt that the robot was not frustrating since they even partly succeeded on guiding it to the different checkpoints without feeling themselves obliged to put a lot of effort into reconstructing the entire CP during trial 2 of the condition (B; Fig. 8).

Participants answers during the debrief support this insight. As the participants felt integrated during the HRI, they attributed positive traits to the robot during the debrief (“striving to finish the task”, “slow but careful”, “cute”, etc.) which may explain the higher likeability results. This is in line with the human asymptotic tendency to attribute positive feedback so that an agent such as a robot can succeed. Thomaz et al. [11] highlighted this tendency that was noticed when a non-expert user was supposed to teach “Sophie” the agent to achieve different tasks in the kitchen in the context of a game-based setup. In such a setup, users assign positive feedback to motivate the agent while it is just a virtual agent. Furthermore, participants could have attributed lower values

Table 1 Summary of hypotheses and results for primary measures

Hypothesis	Objective measures	Subjective measures
Hypothesis 1	Supported partly	Supported partly
Hypothesis 2	Supported	Supported
Hypothesis 3	Supported	Supported
Hypothesis 4	Not supported	Not supported

in terms of the competence construct because we informed them that the robot is conceived to be used as a service robot to help users suffering from Parkinson’s disease when they need to eat. When a robot is conceived to afford a service and the users are informed of this, it has been proven that they adopt an utilitarian way [54] of judgment and a construct such as competence [competence is a subjective measure that has not increased significantly (Fig. 9) causing the hypothesis 1 to be not supported in terms of subjective measures] is related to the service “part” of the HRI (Table 1).

6.2 Hypothesis 2: Dually Coded Feedback to Increase PECP Recall

Hypothesis 2 predicted that combining IUs with the robot’s visible behaviors during CP construction and retrieval improves the user’s remembrance of the PECP where the time needed to recall the rules of the PECP and the task completion time will decrease while the number of recalled rules corresponding to the PECP will increase. It predicts also that combining IUs with the robot’s visible behaviors during CP construction and retrieval will also increase the human’s social face support as well as his perception of the robot’s competence and likeability. As expected, the results supported this hypothesis. Using dually coded feedback helped with ameliorating the objective results in comparison to trial 2 results of setup 1. In fact, users could remember the PECP in a shorter time which led to a decrease in task completion time (Fig. 10). Participants who received dually coded feedback reported significantly higher levels of social face support, competence and likeability (Fig. 11; Table 1).

6.3 Hypothesis 3: Changing IUs Lead to a Worse PECP Remembrance

To verify whether hypothesis 2 higher results during trial 2 of the condition (DCF) were related to the usage of IUs and whether the IUs interfered in the PECP recall process, we elaborated Hypothesis 3. Hypothesis 3 predicted that changing IUs during the recall phase might decrease the user’s remembrance of the PECP where the time needed to recall the rules of the PECP and the task completion time will increase while the number of recalled rules corresponding to the PECP will decrease. Moreover, hypothesis 3 predicted that chang-

ing IUs during the recall phase will decrease the human's social face support as well as his perception of the robot's competence and likeability. For this purpose, we compared trials 2 results of conditions (DCF) and (ADCF).

The results support this hypothesis. When we change the IUs during trial 2 of the condition (ADCF), the objective and subjective results are significantly lower than the trial 2 objective and subjective results of the condition (DCF; Table 1). In fact, users who performed the task during trial 2 (recall phase) in the presence of a set of IUs that it is different than the set used by the robot during trial 1 (encoding phase) reported significantly lower levels of PECP recall in a longer time (Fig. 12). Users assigned lower values for the robot in terms of competence, likeability and social face support in trial 2 of the condition (ADCF; Fig. 13).

As a conclusion, to be useful, a dual code should be preserved. For example, in our case we have robot visible behavior as the pictorial first code related to the instruction (knocking pattern), the second code is the IU. If we suppose that we want the user to remember the instruction needed at time T, and that a robot's behavior (pictorial code) could not be displayed because the goal is to reduce the wrong steps, since steps are costly in terms of robot's energy, time and may cause frustration if they are wrong, one can directly deduce that an IU that it is generated before the robot executes any behavior could be suitable to refresh the non-expert user's memory so that they can remember the adequate composed instruction (knocking pattern) that it is associated with the intended behavior before it is too late and the robot starts executing the wrong behavior.

6.4 Hypothesis 4: Variation-Repeat Technique Backfires

Finally in the context of hypothesis 4, we conducted a comparison between the trials 2 results of conditions (DCF) and (VRDCF). Hypothesis 4 predicted that assigning more than one IU to the same robot's behavior while each IU could not be assigned to more than one robot's behavior improves the user's remembrance of the PECP where the time needed to recall the rules of the PECP and the task completion time will decrease while the number of recalled rules corresponding to the PECP will increase. Moreover, hypothesis 4 predicted that changing IUs during the recall phase will decrease the human's social face support as well as his perception of the robot's competence and likeability.

Results contrast with this hypothesis. Although, our goal was to avoid user boredom, using different IUs assigned for the same robot's behavior backfired and led to inferior PECP recall for a longer time and increased task completion time. In line with the objective results, subjective evaluation dropped in trial 2 of the condition (VRDCF). This degraded performance could be related to the fact that the participant's memory could not retain all of the IUs per one behavior.

The remembrance problem when using the variation-repeat technique was mentioned in 80% of the participant's speech while being debriefed [condition (VRDCF)]. This indicates that using the same IU per one robot's visible behavior is safer if we want to increase PECP recall (Table 1).

7 Implications of the Results

The findings suggest that robots should afford more expressive feedback rather than a mere feedback consisting of the robot's visible behaviors. A more expressive feedback helps increasing the PECP remembrance in order to sustain intrinsic motivation to assign higher subjective evaluation related to the human's perception of the robot's performance.

When users have no feedback other than the robot's visible behaviors, they characterize the robot as non competent and the overall HRI performance is rather stable or degraded because non-expert users cannot remember the PECPs. The current experiment provided users with four setups to evaluate their performance: no dual coded feedback [condition (B)], dual coded feedback [condition (DCF)], altered dual coded feedback [condition (ADCF)] and the variation-repeat technique [condition (VRDCF)]. Users who did not receive dual coded feedback reported the lowest levels of PECP recall and time needed to recall. Users who did receive dual coded feedback reported an increase in PECP recall and thus an increase in overall performance. The somewhat encouraging finding is that when we change the IUs, the objective and subjective results are affected which highlight that IUs usage with minimally designed robots activates the memory related to dual coded rules recall [38]. Furthermore, the effect of the VRDCF technique backfired; that is, providing multiple IUs for the same robot behavior did not provide any additional increase in objective or subjective results which we should, as a conclusion, avoid to do with minimally designed robots if we want to increase PECP recall and the human's perception of the robot.

8 Limitations

Although these results suggest that minimally designed robots should provide non-expert users with dual coded feedback, this approach might have three drawbacks. First, research on dual coding suggests that dual coding is most effective when the human is capable of building referential connections between the information and the codes. Building referential connections between IUs and the robot's visible behaviors includes some cognitive effort. That it is why increasing the number of rules could be difficult to manage.

Secondly, there is another problem, that we did not encounter while conducting our experiment, which is related

to socially anxious non-expert users. In fact, people who suffer from social anxiety have a sickly state that it is activated when they are anxious. Such people predict and imagine the worst when they have to recall information which may lead to drastic performance if we use a dual coded feedback strategy to encode on the memory rules of interaction and later implicitly⁸ drive them to recall these rules [55].

Thirdly, our evaluation focused on testing only the effects of the proposed dual coded method on participants who have low cold-heartedness. In fact, in Aziz-Zadeh et al. [56] suggested that the perception and recognition of IUs are affected by the human's cold-heartedness level. Cold-heartedness is one of the constructs of the personality inventory–revised (PPI-R) [57]. The PPI-R cold-heartedness scale was used as an additional measure of affective empathy where it has been proven that it would negatively correlate with IUs perception. That it is why we plan to extend our work to explore a more diverse set of cold-heartedness levels and the long-term effects of the proposed strategies on PECP recall.

9 Conclusion

As robots move into roles that involve providing users with services, such as cleaning the floor and working in offices, they will need to employ strategies for affording effective expressive feedback to facilitate easy communication with them. In this paper, we described two key feedback strategies DCF and VRDCF based on observations of human–human interactions and social psychology theories. We implemented these strategies on a robot that cooperatively interacts with its users to visit different checkpoints marked on the table. Our results showed that when the robot combined IUs and the robot's visible behaviors, participants completed the task faster and assigned higher ratings for the robot. We also found that using the VRDCF strategy increased the time needed to recall the PECP, as the PECP is recalled incorrectly and the human's perception of the robot's performance was mediocre. We believe that increasing the number of instructions results in a tradeoff between cognitive load and breakdowns related to memory struggles during the recall of the PECP when there is a high number of rules that need to be recalled. This suggests that robots should selectively use these strategies based on the goal of the instruction.

Future work should further explore people who have high cold-heartedness and/or a high social anxiety reaction to such dually-coded feedback using IUs. We also intend to research

how these proposed feedback strategies might influence cognitive load and whether an image combined with each of the robot's behaviors could ameliorate the PECP recall and user perception of the robot's overall performance in terms of likeability, social face support and competence.

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⁸ By “implicit” in this context we mean that the robot has not to tell directly to the human that they introduced a different instruction's version than the actual previously taught instruction. The human can remember indirectly when the IU triggers their memory during the robot's reuse, the previously taught instruction.

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